

# **UNDERSTANDING THE SOCIAL NAVIGATION USER EXPERIENCE**

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# **UNDERSTANDING THE SOCIAL NAVIGATION USER EXPERIENCE**

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*For Michelle. Obviously.*

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## **TABLE OF CONTENTS**

ACKNOWLEDGEMENTS	iv
LIST OF TABLES	xii
LIST OF FIGURES	xiii
SUMMARY	1
CHAPTER 1 INTRODUCTION	4
1.1 Thesis Statement	8
1.2 Contributions	9
1.3 Thesis Organization	12
CHAPTER 2 A USER-CENTERED PERSPECTIVE ON SOCIAL NAVIGATION SYSTEMS	15
2.1 Social Navigation Activities	19
2.2 Decision Making as the Principal Social Navigation Activity	20
2.3 Social Navigation System Components and their Relation to Decision Making	22
2.3.1 Input Data	22
2.3.2 Aggregation Algorithms	24
2.3.3 User Interfaces for Social Navigation and the Efficacy of Social Navigation Systems	26
2.4 Challenges in Employing a User-Centered Perspective for Social Navigation Systems	28
CHAPTER 3 HERDING IN SOCIAL NAVIGATION SYTEMS: A WINDOW INTO THE SOCIAL NAVIGATION USER EXPERIENCE	30

3.1 Herding in a Social Navigation System for an Online Food & Recipe Store	31
3.2 Herding in Moderation of Online Discussion Forums	32
3.3 Herding in a Recommender System	32
3.4 Herding on the Internet and the World Wide Web	33
3.5 Herding on a Music Download Site	34
3.6 Summary	36
CHAPTER 4 A THEORETICAL FOUNDATION FOR UNDERSTANDING THE SOCIAL NAVIGATION USER EXPERIENCE	38
4.1 Psychological Research of Social Influence	39
4.2 Giving, Accepting and Using Advice	42
4.3 Comparing Social Influence and Advice Taking	44
4.4 Economic Research of Herding	48
4.4.1 Experiments of Informational Cascade Behavior	51
4.4.2 An Informational Cascades Perspective on Social Navigation	53
4.5 The Size and Unanimity of Community Data	54
4.6 Hypotheses about the Social Navigation User Experience	55
CHAPTER 5 SOCIAL NAVIGATION FOR END-USER PRIVACY AND SECURITY MANAGEMENT	56
5.1 Addressing End-User Privacy and Security Management with Social Navigation	57
5.1.1 Matching Social Navigation to End-user Security and Privacy Management	60

5.2 Supporting End-User Privacy Management with Social Navigation	61
5.2.1 The Problem: Managing Web-browser Cookies	61
5.2.2 Acumen	62
5.2.3 Lessons Learned from Acumen	66
5.3 Supporting End-user Security Management with Social Navigation	67
5.3.1 Personal Firewall Management	67
5.3.2 Bonfire	69
5.3.3 Lessons Learned from Bonfire	73
5.4 Reflections: Understanding Herding in Privacy and Security Managements	74
5.4.1 Subjective vs. Objective Decisions	75
5.4.1 Informational Cascades in Acumen and Bonfire	77
5.5 Summary	78
CHAPTER 6 AN EXPERIMENT TO INVESTIGATE THE SOCIAL NAVIGATION USER EXPERIENCE: DESCRIPTION	79
6.1 Experiment Motivation: Social Navigation for Online Nonprofit Giving Decisions	79
6.2 Method: Procedure	85
6.3 Scenarios Section / Donation Scenarios	90
6.3.1 Experimental Design	94
6.3.2 Similarities and Differences between this Experiment and Other Experimental Designs	97



6.4 Participant Recruiting	101
CHAPTER 7 AN EXPERIMENT TO INVESTIGATE THE SOCIAL NAVIGATION USER EXPERIENCE: ANALYSES AND FINDINGS	103
7.1 Hypotheses and Divisions among Scenario Conditions	103
7.2 Analysis of Decision Data from All Conditions: Participant Demographic Data & The Dominant Choice in Conditions	106
7.2.1 Participant Demographic Data	106
7.2.2 The Dominant Choice Suggests that Participants Provided Authentic Responses	108
7.3 Analysis of Decision Data from Cascade Conditions	111
7.3.1 Finding: Community Data exerts Information Influence	112
7.3.2 Finding: Herding in a Social Navigation System can be Characterized as Informational Cascades	118
7.3.3 Community Data's Social Influence Reinforces Bias but does not Overcome It	119
7.3.4 Analyzing the Impact of Community Data's Size and Unanimity	122
7.4 Analysis of Decision Data from Non-Cascade Conditions	123
7.4.1 Findings: Social Influence Strength and Egocentric Discounting	124
7.4.2 Differences between Suggesting <i>Yes</i> and Suggesting <i>No</i>	128
7.4.3 Analyzing the of Impact of Community Data's Size and Unanimity	131
7.5 Summary	133

CHAPTER 8 IMPLICATIONS FOR THE DESIGN, USE, AND	
EVALUATION OF SOCIAL NAVIGATION SYSTEMS	136
8.1 Improving the Design of Social Navigation Systems	137
8.1.1 Social Navigation Systems for Subjective and Objective	
Domains	137
8.1.2 Social Navigation Systems for Objective Information	139
8.1.3 Capturing Objective Information and Mitigating	
Informational Cascades	142
8.1.3.1 Mitigating Cascades via Algorithms	143
8.1.3.2 Mitigating Cascades via User Interaction	144
8.2 A General Approach for Evaluating the Social Influence of Social	
Navigation Systems	147
8.2.1 Identifying a Decision and the Most Influential	
Information Sources	148
8.2.2 Developing a Framework for Providing Incomplete	
Information	149
8.2.3 Identifying Critical and Contrasting Decision Points	151
8.2.4 Evaluating Decision Data	155
8.2.5 Benefits of an Evaluation Framework based on Social	
Influence	155
8.2.6 Limitations of an Evaluation Framework based on Social	
Influence	159
CHAPTER 9 IMPACT AND FUTURE WORK	163
9.1 Impact	163

9.2 Future Work: Addressing a Spectrum of Decisions	166
9.3 Future Work: Towards Mindful Use of Social Navigation Systems	167
9.3.1 The Intent and Goals of Social Navigation Systems	168
9.3.2 Long-term Observation and Oversight of Social Navigation Systems	171
REFERENCES	173
VITA	184

## LIST OF TABLES

	Page
<b>Table 2.1:</b> Characteristics of community data types for social navigation systems.	23
<b>Table 6.1:</b> Demographic questions and potential answers.	87
<b>Table 6.2:</b> Nonprofit giving questions and potential answers.	89
<b>Table 6.3:</b> Categories for nonprofit organizations and examples used in experiment's nonprofit giving questions.	89
<b>Table 6.4:</b> Feedback questions on decision-making scenarios.	94
<b>Table 6.5:</b> Values for the independent variable <i>data configuration</i> . Variable fully qualifies the number of visible ratings, ratings' values, and whether the ratings agree or disagree with the community data.	97
<b>Table 7.1:</b> Summary of participants' demographic data.	107
<b>Table 7.2:</b> Significance values for decision data from cascade conditions for ratings configuration and community data size and unanimity.	122
<b>Table 7.3:</b> ANOVA analysis of factors for non-cascade conditions.	132
<b>Table 8.1:</b> Characteristics of community data.	146

## LIST OF FIGURES

	Page
<p><b>Figure 2.1:</b> Examples of social navigation systems. Clockwise from top-left: (a) Digg, a website where users can vote on (“digg”) and discuss stories; stories are displayed based on the number of diggs that they receive. (b) The Alexa web toolbar, which displays information about the popularity of a website a user is visiting. (c) The Amazon website, which employs many different forms of social navigation, including recommendations, lists of most popular items, and item ratings and comments. (d) A list of the most popular stories on <i>The New York Times</i> website.</p>	17
<p><b>Figure 4.1:</b> Applying psychological frameworks to understand the social navigation user experience. Social influence research is useful for understanding simple social navigation, and advice-taking research is useful for understanding complex social navigation.</p>	47
<p><b>Figure 4.2:</b> Connecting social influence at the individual level to herding at the group level. Normative influence leads to irrational herding, and informational influence leads to informational cascades.</p>	49
<p><b>Figure 5.1:</b> Screenshots of the Acumen system. From top left clockwise: (a) the Acumen Internet Explorer toolbar on The New York Times website; (b) the Acumen Firefox Sidebar on the MSNBC website; and (c) detailed community data about a website’s cookies from the Acumen Firefox Sidebar.</p>	63
<p><b>Figure 5.2:</b> Screenshots of the Bonfire system. Top: alert window that enables users to employ community data to make firewall management decisions; bottom: Bonfire’s summary interface for viewing firewall decisions in relation to the community.</p>	70
<p><b>Figure 6.1:</b> The technology-assisted donation lifecycle.</p>	80

<b>Figure 6.2:</b>	<i>Charity Navigator</i> webpage for a nonprofit organization.	83
<b>Figure 6.3:</b>	Scenario or decision trial in the nonprofit experiment: a participant is asked to decide whether he would make a donation to this nonprofit. Two data sources are available: (a) watchdog financial efficiency ratings and (b) community data from a social navigation system. One watchdog rating is visible (NEL), and two watchdog ratings are hidden (ABE, SUR). The community data disagrees with the watchdog rating, and hence the participant must choose to follow either the watchdog rating or the community data.	90
<b>Figure 6.4:</b>	Example 1 in the scenarios section introduces participants to watchdog financial efficiency ratings.	92
<b>Figure 6.5:</b>	Example 2 in the scenarios section introduces participants to temporarily missing financial efficiency ratings and reasons they might be missing.	93
<b>Figure 6.6:</b>	Example 3 in the scenarios section introduces participants to community data and instills the belief that other people may have seen ratings that they cannot see.	93
<b>Figure 6.7:</b>	Examples of agreement between watchdog financial ratings and community data (top) and disagreement (bottom).	96
<b>Figure 7.1:</b>	Summary of participants' answers to the question "In the scenarios, how did you make decisions about whether you'd donate to a nonprofit organization?"	110
<b>Figure 7.2:</b>	Comparing social influence in cascade conditions when one, two, or three rating are visible.	113

<b>Figure 7.3:</b>	Comparing social influence in cascade conditions when one rating is visible and when two or three ratings are visible. Results show that social influence—making decisions that agree with the community consensus and disagree with rating(s) seen—is stronger when only one rating is visible as compared to when two or three ratings are visible. Error bars denote 95% confidence interval.	114
<b>Figure 7.4:</b>	Comparing social influence in cascade conditions when one, two, or three ratings are visible.	115
<b>Figure 7.5:</b>	Comparing social influence in cascade conditions when one rating is visible vs. 2 or 3 ratings are visible.	115
<b>Figure 7.6:</b>	Social influence in cascade conditions organized by the posited signal strength for each set of ratings. Posited signal strength includes both the expected value of a set of ratings and the uncertainty associated with the ratings.	117
<b>Figure 7.7:</b>	Decision data for cascade trials when community data suggests <i>Yes</i> and ratings suggest <i>No</i> .	120
<b>Figure 7.8:</b>	Decision data for cascade trials when community data suggests <i>No</i> and ratings suggest <i>Yes</i> .	120
<b>Figure 7.9:</b>	Social influence in conditions when one, two, or three watchdog ratings are visible and the ratings suggest the same decision as the community data. When two ratings are visible, they are split and the direction of the community data is assigned randomly; when three ratings are visible, the ratio is always two in one direction and one in the opposite direction.	125
<b>Figure 7.10:</b>	Social influence across conditions when one, two, or three watchdog ratings are visible and the ratings suggest the same decision as the community data. Influence is measured across community data sizes and unanimity.	125

<b>Figure 7.11:</b>	Decision data for non-cascade conditions when expected decision is <i>No</i> .	129
<b>Figure 7.12:</b>	Decision data for non-cascade conditions when expected decision is <i>Yes</i> .	129
<b>Figure 7.13:</b>	Decision data based on community data size and unanimity for non-cascade conditions when expected decision is <i>No</i> .	130
<b>Figure 7.14:</b>	Decision data based on community data size and unanimity for non-cascade conditions when expected decision is <i>Yes</i> .	130
<b>Figure 7.15:</b>	Rates of conformity when participants saw two ratings, each of which had a different value. Interaction effect occurs when both community data size and unanimity are high. Interaction effect significance is $p < 0.03$ , error bars are $p < 0.1$	133
<b>Figure 8.1:</b>	Decision space for nonprofit choice experiment.	153



## SUMMARY

A social navigation system collects data from its users—its community—about what they are doing, their opinions, and their decisions, aggregates this data, and provides the aggregated data—community data—back to individuals so that they can use it to guide behavior and decisions. Social navigation systems empower users with the ability to leverage social information on a much larger and faster scale than they can in the physical world. With social navigation systems, users can “see” what many, many other people have done without directly interacting with or observing them and can do so at a time when it is most beneficial to them.

The popularity of social navigation systems indicates that both designers and users perceive value in them, but evaluations of social navigation systems yield surprising and mixed results. These findings suggest that while social navigation systems can lead users to good decisions and outcomes, they can also lead users to unexpected and potentially undesirable decisions and outcomes. In this thesis, I document my investigation of the user experience for social navigation systems that employ activity data. I define the social navigation user experience to be how users perceive, make sense of, and employ community data from social navigation systems.

I make three main contributions in this thesis. First, I synthesize social navigation systems research with research in social influence, advice-taking, and informational cascades to construct hypotheses about the social navigation user experience. These hypotheses posit that community data from a social navigation system exerts informational influence on users, that users egocentrically discount community data, that herding in social navigation systems can be characterized

as informational cascades, and that the size and unanimity of the community data correspond to the strength of the community data's influence.

The second contribution of this thesis is an experiment that evaluates the hypotheses about the social navigation user experience; this experiment investigated how a social navigation system can support online charitable giving decisions. The experiment's results support the majority of the hypotheses about the social navigation user experience and provide mixed evidence for the other hypotheses. The results show that the social navigation system's community data exerted informational influence on participants and that the herding in social navigation systems can be characterized as informational cascades. The results suggest that participants egocentrically discounted community data; however, because the experiment was not designed to directly measure egocentric discounting, it is not possible to verify this hypothesis. The experiment's results show that the unanimity of the community data is a significant factor in the effect that the community data has on participants' decisions, but that the size of the community data was only significant in some instances. Finally, the results indicate that participants were skeptical of making a donation in general, and the community data was much more influential when reinforcing this skepticism as compared to overcoming it.

The implications that arise from the experiment's findings compromise the final contribution of this thesis. Broadly, these implications concern improving the design of social navigation systems and developing a general framework for evaluating the social influence of social navigation systems. The approach to improving social navigation systems is grounded in the development of methods to capture, aggregate, and represents objective information rather than actions or decisions. A general framework for evaluating the social influence of social navigation systems derives from the experimental design of the nonprofit choice

experiment; this framework standardizes the inputs, outputs, and analyzes for social navigation systems. The benefits of this framework include comparing social navigation systems within and across domains and comparing results from evaluations of social navigation experiments to results from experiments in social influence and informational cascades.

# **CHAPTER 1**

## **INTRODUCTION**

People are innately social creatures, and the ways in which people leverage social information to form opinions, guide behavior, and make decisions has been and continues to motivate many areas of research (Bandura, 1986; Fiske & Taylor, 1991; Taylor, 2007). It is no surprise, then, that interactive computational systems have arisen to help people leverage social information; these systems are called social navigation systems (Höök, Benyon, & Munro, 2003). A social navigation system collects data from its users—its community—about what they are doing, their opinions, and their decisions, aggregates this data, and provides the aggregated data—community data—back to individuals so that they can use it to guide behavior and decisions. Social navigation systems empower users with the ability to leverage social information on a much larger and faster scale than they can in the physical world. With social navigation systems, users can “see” what many, many other people have done without directly interacting with or observing them and can do so at a time when it is most beneficial to them.

Researchers have built systems that enable users to navigate socially in numerous domains; these domains include editing and reading documents (Hill, Hollan, Wroblewski, & McCandless, 1992), reading newsgroup messages (Resnick, Neophytos, Suchak, Bergstrom, & Riedl, 1994), exploring an online food recipe store (Svensson et al., 2001), browsing the Internet (Wexelblat & Maes, 1999), and finding citations for research papers (McNee, Kapoor, & Konstan, 2006). In addition, many highly popular websites use social navigation

systems either as a primary or complementary component of their site, including the online store Amazon<sup>1</sup>, the technology news and discussion website Slashdot<sup>2</sup>, and the websites for the news organizations CNN<sup>3</sup>, BBC<sup>4</sup>, and *The New York Times*<sup>5</sup>.

The popularity of social navigation systems indicates that both designers and users perceive value in them, but evaluations of social navigation systems yield surprising and mixed results. Benefits of social navigation systems include helping users find items of interest more quickly (Wexelblat & Maes, 1999) and fostering awareness and social interaction among users that are employing the system at the same time (Svensson et al., 2001). However, social navigation systems can also produce suboptimal or undesirable results. In particular, herding behavior has been found to be a common problem in numerous social navigation systems (Cosley, Lam, Albert, Konstan, & Riedl, 2003; Goecks & Mynatt, 2005b; Lampe & Resnick, 2004; Svensson et al., 2001), and herding can lead users to behaviors and decisions that they later regret, find little value in, or find to be incorrect (Salganik, Dodds, & Watts, 2006; Svensson et al., 2001).

Instead of attesting to the value of social navigation systems, these findings suggest that a closer examination of these systems and their value to users is needed. Recent research has argued that focusing on user interfaces (Herlocker, Konstan, Terveen, & Riedl, 2004) and user tasks (McNee, Kapoor et al., 2006; McNee, Riedl, & Konstan, 2006b) are promising areas of research for improving

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<sup>1</sup> <http://www.amazon.com>

<sup>2</sup> <http://slashdot.org>

<sup>3</sup> <http://www.cnn.com>

<sup>4</sup> <http://www.bbc.co.uk>

<sup>5</sup> <http://www.nytimes.com>

social navigation systems. Nonetheless, a rigorous investigation of how users employ community data from social navigation systems has not been performed. Without such an investigation, it is difficult to understand how to improve user interfaces for social navigation systems, how to evaluate the efficacy of a social navigation system and how to compare multiple systems, and where and when to deploy social navigation systems to benefit users.

These observations motivate this thesis. In this thesis, I document my investigation of the user experience for social navigation systems that employ activity data. I use the phrase *user experience* because it encompasses a wide range of potential interactions between users and a social navigation system's community data. I define the social navigation user experience to be how users perceive, make sense of, and employ community data from social navigation systems. I largely limit my focus to social navigation systems that collect, aggregate, and display activity data—data about others' behavior and decisions—because activity data is the simplest form of community data and thus a logical starting point for studying the social navigation user experience. When a social navigation system collects and displays only activity data, users cannot interact with each other; this form of social navigation is called *indirect* social navigation, as compared to direct social navigation, where users can interact with each other (Dieberger et al., 2000).

My investigation of the social navigation user experience began with efforts to understand its foundations. Dourish has argued “that social navigation is an interactive phenomenon rather than a class of technology....” (Dourish, 2003). I concur with this conceptualization of social navigation but generalize further; I argue that social navigation is a unique cognitive activity and a set of behaviors that occurs not only in social navigation systems but anytime individuals can observe others' actions or decisions and use these observations when making

their own decisions. In fact, previous theorizing about social navigation draws parallels between socially-aided navigation in the physical world and what social navigation systems can facilitate in the digital world (Dieberger et al., 2000; Svensson et al., 2001).

Because I consider social navigation to be a general cognitive activity and a set of behaviors that occurs not only online with the help of social navigation systems but also offline without help from technology, it is beneficial to identify research that has studied offline behavior that is similar to social navigation and use this research to ground and foster investigation of the social navigation user experience. This is the approach that I employ in my thesis.

I have performed an extensive review of behavioral and social science research and identified three bodies of research that bear strong similarities to social navigation systems: social influence (Bond & Smith, 1996), advice-taking (Bonaccio & Dalal, 2006), and informational cascades (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Welch, 1992). I argue that these three bodies of research should undergird a understanding of the social navigation user experience because they provide knowledge about how people behave and make decisions in situations that are nearly identical to those that users of social navigation systems encounter. In brief, the situation common to these three bodies of research and social navigation systems is as follows: an individual encounters a decision to be made and can see what other people have decided before him; the natural behavior in this situation is to use the choices of others as well as any personal information he has to make a decision. The opportunity to see what others have chosen before making a decision is the key feature of this situation and, notably, is the principal function of a social navigation system.

Research in social influence, advice-taking, and informational cascades clearly demonstrates that the opportunity to see what others have done before making a decision often profoundly influences the decision. In all bodies of research, individuals often make choices that are the same as or quite similar to the choices that others have made, oftentimes ignoring information that suggests a different choice. However, each body of research contributes a unique perspective on how individuals employ and are influenced by observing others' decisions. Social influence research indicates that there are two types of social influence, normative social influence and informational social influence, and numerous factors impact the type of social influence that occurs in a given instance. Advice-taking research shows that individuals use many techniques to weigh others' decisions and arrive at a final decision based on both their own and others' decisions. Finally, informational cascades research shows that many sub-optimal outcomes occur when social influence is amplified or unchecked.

My thesis statement discusses how I leverage these bodies of research toward the advancement of social navigation systems.

### **1.1 Thesis Statement**

*Understanding the social navigation user experience—how users perceive, make sense of, and employ community data from social navigation systems—for systems that employ activity data can be accomplished by employing a multidisciplinary perspective. This perspective—driven by research in social navigation systems, social influence, advice-taking, and informational cascades—predicts that (a) community data from a social navigation system exerts informational influence; (b) herding in social navigation systems can be characterized as informational cascades; (c) users ego-centrally discount*



*community data; and (d) the size and unanimity of community data correlate with the impact of community data on decision making.*

## **1.2 Contributions**

There are three main contributions that derive from this thesis statement. First, I synthesize social navigation systems research with research in social influence, advice-taking, and informational cascades to construct hypotheses about the social navigation user experience. Second, I empirically evaluate these hypotheses via an experiment and thereby develop a robust understanding of the social navigation user experience. Finally, I discuss how an understanding of the social navigation user experience can inform and improve the design, deployment, and evaluation of social navigation systems. I discuss each of these contributions in turn.

My first contribution is a set of five hypotheses about the social navigation user experience. To derive hypotheses about the social navigation user experience, I applied each perspective—social influence, advice-taking, and informational cascades—in order to understand how users might experience community data from a social navigation system.

The principal hypotheses that drive the thesis statement arise from a social influence and informational cascades perspective. There are two types of social influence, informational influence and normative influence (Deutsch & Gerard, 1965). *Informational influence* occurs when an individual employs community data as a source of information, and *normative influence* occurs when an individual employs community data as a source of social standards. Both types of influence guide both tacit and explicit choices; however, each type arises from unique motivations and thought processes that can lead to different choices in the same context. The hypothesis that derives from a social influence perspective

states that community data exerts informational influence rather than normative influence on users.

The hypothesis that derives from an *informational cascades* (Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992) lens predicts that herding in social navigation systems arises due to informational influence rather than normative influence. This hypothesis states that when users interpret community data as a source of information, they may sometimes ignore their own information and make the choice that matches the community consensus. (The community consensus is clear from the community data.) When this occurs, the herding in social navigation systems are informational cascades. Informational cascades, then, are driven by informational influence. Cascades arise when an individual infers information from others' choices and uses the inferred information to guide his choice; such inferences often lead to herding. Conversely, herding driven by normative influence is simpler; in this type of herding, individuals herd to derive the benefits of conforming to social conventions or to avoid the consequences of nonconformity.

Three additional hypotheses arise from this multidisciplinary perspective on the social navigation user experience. The hypothesis that derives from an advice-taking perspective predicts that users value their initial choice more highly than they do others' choices. Because a system's community data represents others' choices, an individual using a social navigation system reaches a final decision by combining his initial choice with others' choices. I hypothesize that his final choice will be closer to his initial choice than to others' choices. This phenomenon—discounting others' decisions in relation to one's own—is termed *ego-centric discounting*, and it is one of the most robust findings in the advice-taking literature (Bonaccio & Dalal, 2006).

My final two hypotheses concern the size and unanimity of the community data. The *community data's size* is the number of people whose data is represented, and the *community data's unanimity* is the unanimity in the data. I hypothesize that both the size and unanimity of community data correlates with its impact on users' decisions. A community data's size and unanimity are common factors in the bodies of research that drive my analysis of the social navigation user experience.

My second contribution is the design and completion of an experiment that evaluates these hypotheses by studying user decision making for the nonprofit giving domain. In the experiment, participants are asked to place themselves in the role of potential donors and make a series of decisions regarding whether they would make a donation to different nonprofit organizations. For each nonprofit that a participant is asked to make a decision for, she is provided with two types of data, private information about the organization's efficiency and community data from a social navigation system. The experiment's structure employs techniques from informational influence experiments (Baron, Vandello, & Brunsman, 1996; Deutsch & Gerard, 1965) and informational cascades experiments (Anderson & Holt, 1997, 2006). Results from this experiment validate my two principal hypotheses, provide mixed evidence for my other three hypotheses, and yield surprising insight into the unequal impact of community data based on decision biases.

The final contribution applies the knowledge gained from this experiment to the design, deployment, and evaluation of social navigation systems. I apply knowledge about the social navigation user experience to the development of novel user interface techniques for social navigation systems that mitigate informational cascades, which often leads users to suboptimal decisions and can produce significant negative consequences.

Knowledge of the social navigation user experience can also provide guidance about the domains in which social navigation is likely to be most useful. Currently, there is little guidance beyond case studies about the utility of social navigation systems in different domains. However, knowledge of the social navigation user experience suggests that domain-specific factors such as knowledge distribution, decision biases, and incentive structures are likely to contribute to the success or failure of a social navigation system.

Finally, I also discuss how the experimental design and analysis employed in this thesis can serve as a general method for evaluating social navigation systems regardless of the domain. This experimental approach produces data that is system and domain-agnostic and thus can be used to compare systems in the same domain or systems in different domains.

### **1.3 Thesis Organization**

The organization of this thesis parallels the thesis statement and contributions. Chapters 2, 3, and 4 develop a foundation for understanding the social navigation user experience. Chapter 2 reviews previous research on social navigation systems from a user-centered perspective and identifies four challenges that arise from this perspective: (a) creating systems that support the canonical activity in social navigation, decision making or, specifically, selecting from amongst a set of choices; (b) understanding the social navigation user experience—how users perceive, make sense of, and employ community data; and (c) evaluating the efficacy of social navigation systems.

Chapter 3 argues that herding behavior in social navigation systems can provide a window into the social navigation user experience. This chapter discusses instances of herding behavior in several different social navigation systems and the consequences of herding. The chapter concludes by identifying

key questions about herding and about the social navigation user experience, and these questions serve to ground the discussion in Chapter 4. Chapter 4 engages the social navigation experience on a theoretical level. In this chapter, I synthesize research in social navigation systems with research in social influence, advice-taking, and informational cascades to develop broad hypotheses about the social navigation user experience.

In Chapter 5, I reflect on social navigation systems that I developed for end-user privacy and end-user security management through the lens of the social navigation user experience. This lens provides insight into the successes and failures of each system and how similar systems might be improved. A central focus in this chapter is the prevention of informational cascades in social navigation systems applied to end-user privacy and security management.

Chapters 6 and 7 describe and discuss results from the nonprofit choice experiment, an experiment to operationalizes and evaluate my hypotheses about the social navigation user experience. Chapter 6 describes the experiment design in great detail. Particular focus is paid to the conditions in the experiment and how decision data from the conditions can yield insight into critical decisions. The chapter concludes with a full list of hypotheses for the experiment. Chapter 7 reports the results of the experiment and evaluates each hypothesis based on experimental data.

Chapters 8 and 9 apply and reflect on the knowledge of the social navigation user experience gained in the preceding chapters. Chapter 8 argues that, in particular domains, social navigation systems can be improved by focusing on the capture, aggregation, and representation of objective information rather than actions or decisions. Chapter 8 also discusses a general evaluation method for social navigation systems. Chapter 9 reflects back on the thesis as a whole. This

chapter discusses the contributions of this thesis and future work that can be explored as a result of the findings in this thesis. Chapter 9 and the thesis conclude by arguing for the mindful use of social navigation systems. The research in this dissertation shows that social navigation systems are not neutral technologies—they promote some behaviors and choices and mitigate others—and hence it may be useful to make the desired goals of a social navigation system explicit and consider how best to employ a system to achieve those goals.

## **CHAPTER 2**

### **A USER-CENTERED PERSPECTIVE ON SOCIAL NAVIGATION SYSTEMS**

Dourish and Chalmers introduced the concept of social navigation while discussing methods for navigating information spaces (Dourish & Chalmers, 1994). In this nascent conception, individuals navigating socially move through an informational space based on markers generated by other people's activities. Social navigation, then, differs markedly from navigating a space based on physical or informational markers. Social navigation systems support the activity of social navigation by enabling a user to see what other people have been doing or saying by automatically capturing, aggregating, and displaying the behavior and activities of its community of users (Höök et al., 2003). For example, a social navigation system might highlight "paths" that lead to popular webpages about a particular subject, highly rated posts in a discussion forum, frequently downloaded food recipes from an online cookbook, or recommendations for songs that an individual may be interested in purchasing from a music store.

Researchers have built systems that enable users to navigate socially in numerous domains; these domains include editing and reading documents (Hill et al., 1992), reading newsgroup messages (Resnick et al., 1994), exploring an online food recipe store (Svensson et al., 2001), browsing the Internet (Wexelblat & Maes, 1999), navigating online educational lectures (Mertens, Farzan, & Brusilovsky, 2006), collaborating around information visualizations (Heer, Viegas, & Wattenberg, 2008), and finding citations for research papers (McNee,

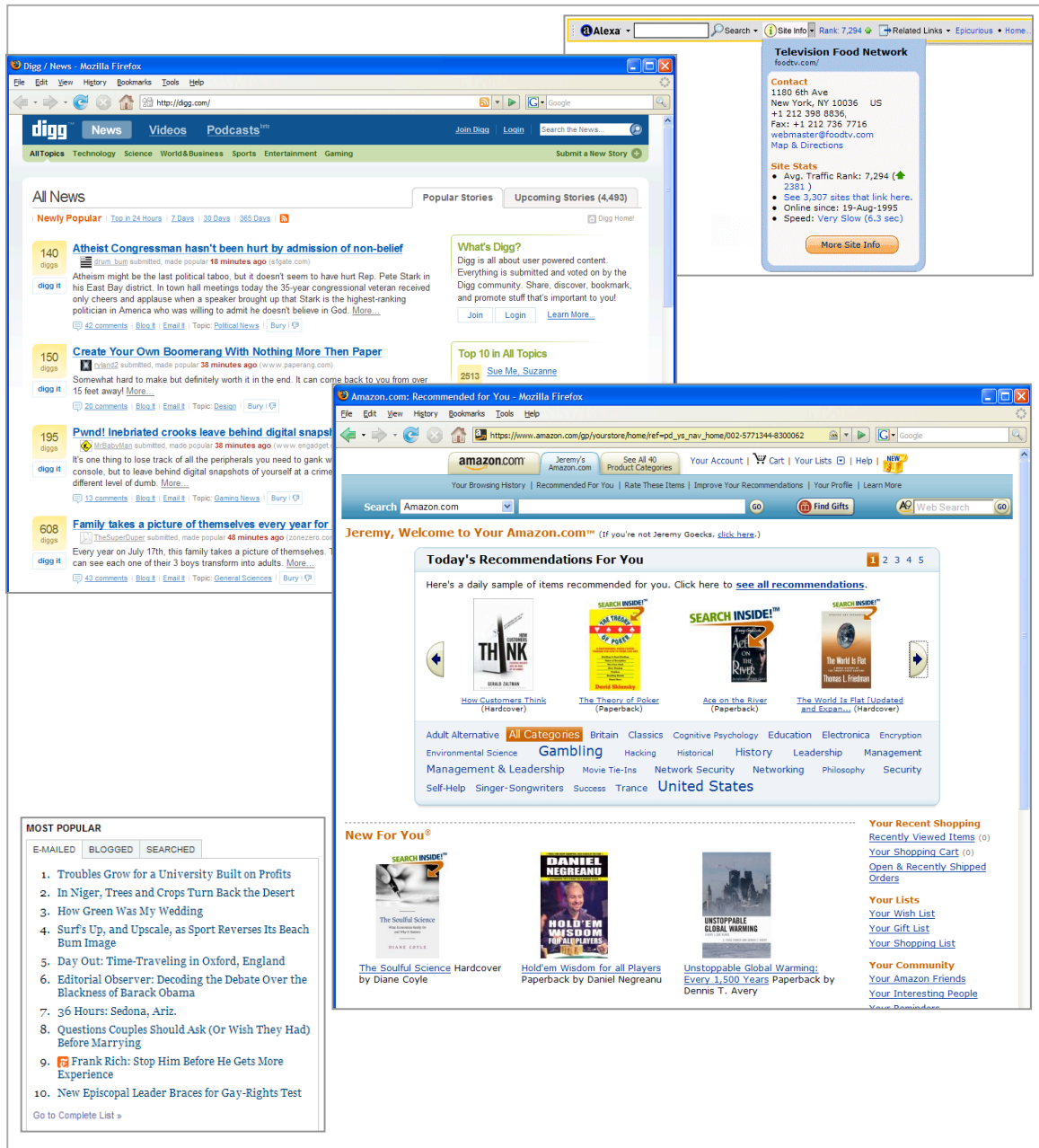
Kapoor et al., 2006). In addition, many highly popular websites use social navigation systems either as a primary or complementary component of their site, including the online store Amazon<sup>6</sup>, the technology news and discussion website Slashdot<sup>7</sup>, and the websites for the news organizations CNN, BBC, and *The New York Times*. Figure 2.1 shows a number of commercial social navigation systems.

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<sup>6</sup> <http://www.amazon.com>

<sup>7</sup> <http://slashdot.org/>





**Figure 2.1.** Examples of social navigation systems. Clockwise from top-left: (a) Digg, a website where users can vote on ("digg") and discuss stories; stories are displayed based on the number of diggs that they receive. (b) The Alexa web toolbar, which displays information about the popularity of a website a user is visiting. (c) The Amazon website, which employs many different forms of social navigation, including recommendations, lists of most popular items, and item ratings and comments. (d) A list of the most popular stories on *The New York Times* website.

The purpose of this chapter is to analyze past research in social navigation systems research from a user-centered perspective. I discuss the activities for which users employ social navigation systems and the domains that social navigation systems have been utilized in. I also discuss past research that has endeavored to measure the efficacy of social navigation systems; I focus on relating the three basic components of a social navigation system—input, aggregation algorithm, and output—to the impact that a system has on users. Based on these discussions, I identify a unique subset of challenges for employing social navigation systems, and these challenges drive the investigation of the social navigation user experience. In brief, these challenges are:

1. using social navigation systems to support decision making;
2. understanding how users employ data from social navigation systems;
3. evaluating how well social navigation systems meet users' needs.

Before proceeding further, it is useful to define the terms *community* and *community data* as they relate to social navigation systems; I use these terms extensively in the remainder of this dissertation. I define the term *community* to mean the set of users who utilize and contribute data to a social navigation system, and *community data* is the aggregated user data that a system presents for use in social navigation. I use the term *community data* rather than *community information* in order to draw a clear distinction between the data that a system provides and the information that users interpret from that data. This distinction is a focus of this thesis.

## 2.1 Social Navigation Activities

An initial step toward the development a user-centered perspective on social navigation systems is identifying and discussing the activities that users engage in when they navigate socially.

I argue that three general activities comprise social navigation (Goecks & Mynatt, 2005a). These activities are (1) becoming aware of a choice or an available path; (2) seeking information about particular choices and paths; and (3) weighing available information—oftentimes community data—and making an informed decision. Taken together, I argue that social navigation is the repeated execution of the three activities above while maintaining awareness of others' activities and using the information derived from such awareness to guide each activity. This conceptualization of social navigation is quite similar to that proposed in (Riedl & St. Amant, 2003).

Now consider how social navigation systems support each of the three activities that comprise social navigation. First, a social navigation system may help individuals navigate a large information space by filtering or ranking items based on community data; collaborative filtering systems [e.g. (Goldberg, Nichols, Oki, & Terry, 1992; Resnick et al., 1994) ] and Internet search engines [e.g. Google<sup>8</sup> and Alexa<sup>9</sup>] use community data to filter and rank order items. Lists of most popular webpages or forum posts, most purchased items, or recommended products are example outputs from social navigation systems that filter and rank items in order to help users' awareness of particular items.

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<sup>8</sup> <http://www.google.com>, see (Page, Brin, Motwani, & Winograd, 1998) for a description of how the Google search engine leverages community data.

<sup>9</sup> <http://www.alexa.com>

Alternatively, a social navigation system may, based on others' actions, highlight particularly useful or salient information so that it draws users' attention. Harrison and Dourish's "space to place" model articulates this approach (Harrison & Dourish, 1996); in this model, users transform or augment a space via their actions, turning it into a place. The transformations and augmentations that users enact on a space provide evidence of how others have interacted and utilized the space towards individual and shared goals. Websites (Svensson et al., 2001) and discussion spaces (Viegas & Donath, 1999) often use this approach. As with filtering, raising awareness is the principle user activity that the "space to place" model supports.

Finally, a social navigation system may endeavor to directly support decision making. Reputation systems (Resnick, Kuwabara, Zeckhauser, & Friedman, 2000) are an example of a decision support systems. Reputation systems collect and make visible community feedback about interactions (often transactions) with an individual (or company) has made in the community, and the feedback serves as the individual's reputation. When an individual considers interacting (e.g. buying an item) from another person, he can use the person's reputation as information to help him decide whether he wants to interacting with that person.

## **2.2 Decision Making as the Principal Social Navigation Activity**

A closer examination of the three activities that comprise social navigation suggests that they are, in fact, all in service of decision making. When a system filters, ranks, or highlights items, it is helping users direct their attention to particular items and, ideally, helping users identify a subset of items from which they will make their final selection. Thus, the purpose of a social navigation system is to help users make decisions that will culminate in the selection of an

item; of course, the selection of an item is clearly the most salient decision that a user makes.

Other analyses also suggest that decision making is a central activity of social navigation. Wexelblat and Maes have argued that the kind(s) of information provided by a social navigation system—what has been done, who has done it, why they did it, and how they did it—can support particular user tasks (Wexelblat & Maes, 1999). The majority of social navigation systems provide mostly or exclusively *what* information (e.g. ratings, lists of most read, listened to, or download items) because it is easy to collect, aggregate, and display, and Wexelblat and Maes argue that *what* information best supports information seeking and “guidance support” or decision making. Dourish concurs that within the context of social navigation, the term ‘navigation’ is best understood to be an information-seeking activity (Dourish, 2003). Finally, Gintis has argued that the brain is best understood to be a decision-making organ, and that many human activities—including information seeking—can be conceptualized as deciding between or selecting actions to perform (Gintis, 2007).

Of course, information seeking and decision making are often closely related. When seeking information, users repeatedly make decisions about where to look next and whether to read an item in depth. In addition, decision making often motivates information seeking because information sought is frequently used to make a decision. Ultimately, I argue that decision making is a more useful focal activity than information seeking because decision making more often drives information seeking.

Based on this discussion, I argue that decision making is the principal activity that users engage in during social navigation. *Thus, one challenge that I address*

*in this thesis is bringing a decision-making perspective to bear on social navigation systems.*

## **2.3 Social Navigation System Components and their Relation to Decision Making**

Three principal components comprise a social navigation system: input data, algorithms for data aggregation, and the display and use of the aggregated community data. I discuss each of these components, highlighting the advantages and disadvantages of choices for each component and the relationships between choices and the activities and domains to which a system is applied.

### **2.3.1 Input Data**

The input to a social navigation system is the raw data that the system collects. Input data for a social navigation system can be of multiple types; the most common types are activity data, ratings, and free text. Examples of activity data for a shopping website include articles read, hyperlinks clicked on, and items purchased. Individuals generate activity data as a byproduct of performing actions, and the system records this data by instrumenting digital environments to record actions taken. Many systems enable individuals to actively rate items (Resnick et al., 1994), transactions (Resnick et al., 2000), or even people (Terveen & McDonald, 2005). Other social navigation systems enable users to submit free text, often in addition to activity data and ratings; free text is often used to capture comments and conversations about an object (or item or person).

Table 2.1 provides an analysis of these three input data types and tagging (discussed below) along four dimensions: (1) implicit or explicit data collection; (2) user burden; (3) ease of aggregation; and (4) information expressiveness. Users generate activity data as a result of their normal actions, and hence activity

**Table 2.1** Characteristics of community data types for social navigation systems.

	<b>Data Collection</b>	<b>User Burden</b>	<b>Aggregation</b>	<b>Expressiveness</b>
<b>Activity Data</b>	Implicit	Low	Easy	Low
<b>Ratings</b>	Explicit	Moderate	Easy	Moderate
<b>Free Text</b>	Explicit	High	Hard	High
<b>Tagging</b>	Explicit	Moderate	Moderate	Moderate-High

data is collected as an implicit byproduct of those actions. In contrast, users must take intentional action to generate explicit data; examples of explicit data include rating an item and typing a comment. Some data types impose a higher burden on users than others. Implicit data imposes a low burden on users, but explicit data imposes a higher burden on users. Moreover, different forms of explicit data are more burdensome than others; rating an item takes less effort than writing a review of the item. Most data types are amenable to aggregation because one datum can be compared to another, but there is a notable exception: free text is not easily aggregated.

Finally, data types differ markedly in their capacity to express information. Activity data has limited expressiveness because it conveys little information. Activity data shows what actions were performed, but not why they were performed; hence an individual must infer the motivations behind activity data. This inference process can be quite difficult because many social navigation systems provide relatively little context or additional information from which an individual might make better inferences. Explicit data is more expressive than implicit data because it often explains why a particular action was taken. An important observation is that the burden placed on a user during the generation of data closely correlates with information content; the more effort required to create the data, the more expressive—and likely more useful—the data will be.

A type of input data for social navigation systems that is becoming increasingly popular is tagging. Tagging is the practice of applying multiple, short words or

phrases to describe an item; each word or phrase is an independent tag that describes the item. Tags are free text, but are amenable to aggregation because they are short and can be easily compared. Individuals may tag items so that they can find them easily in the future, and tagging systems may aggregate individual tags to facilitate the goals discussed in the previous section, especially filtering, searching and navigating a collection of objects (Dourish et al., 2000; Marlow, Naaman, boyd, & Davis, 2006; Shilad et al., 2006). Popular tagging systems include del.icio.us<sup>10</sup>, a bookmark tagging system, and Flickr<sup>11</sup>, a photo tagging system. Tagging is a potential “sweet spot” among input data types. Tagging is an explicit data type that imposes a low burden on users, is easily aggregated, and has moderately high expressivity. Thus, tagging balances the typical tradeoff between user burden and expressivity better than other data types.

In this thesis, I focus on analyzing and understanding the user experience for social navigation systems that employ only activity data. I limit my focus to systems that employ activity data for multiple reasons. Systems that employ activity data are the simplest form of social navigation system and thus quite amenable to study. In addition, there is very little understanding of the social navigation user experience for these systems. Because systems that employ activity data are simple and unstudied from a user experience perspective, they are an excellent subject for investigation.

### **2.3.2 Aggregation Algorithms**

Most social navigation systems aggregate input data and present a summarization of the aggregation as community data. Aggregation is the process

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<sup>10</sup> <http://delicious.com/>

<sup>11</sup> <http://www.flickr.com/>



by which a social navigation system includes, excludes, and weights input data to generate community data. Aggregating input data is useful because users rarely want to look at each individual datum, and aggregation obviates this problem by presenting a summarization that encompasses multiple data points. For example, users may want to view data about a particular item or view data generated during a particular time period. Aggregation is independent of data type; if a data type can be aggregated (i.e. can be compared), any aggregation method can be applied to the data.

A key aggregation challenge for social navigation systems is selecting a group of users from which to draw data for aggregation. Most aggregation algorithms have the following structure:

1. identify a group of selected users from the community;
2. weight selected users based on a criterion;
3. average weights from selected users.

Thus, there are two dimensions along which aggregation algorithms can vary. First, different algorithms can select different users; second, different algorithms can weight users differently. At opposite ends of these dimensions are the two very popular aggregation algorithms equal-weight, inclusive aggregation [e.g. (Goecks & Mynatt, 2005b; Wexelblat & Maes, 1999)] and collaborative filtering (Resnick et al., 1994). The equal-weight inclusive aggregation (EI) algorithm includes all data from all users and weights all data equally. In contrast, a collaborative filtering (CF) algorithm personalizes the aggregation result to an individual by selecting a set of neighbors that are similar to an individual and weighting data from each neighbor based on how similar the neighbor is to the individual.

There is limited research on the value that users find in aggregation algorithms. Cosley et al. have verified this assumption, showing that users expressed more satisfaction when a recommendation system provided accurate ratings as compared to when it provided inaccurate ratings (Cosley et al., 2003). Senecal and Nantel have studied the impact of a recommendation system on users' decisions; they demonstrate that users select products significantly more often when they are recommended by a system and that recommendations assumed to be from a personalized recommendation system were more influential than recommendation from an EI system or from a group of experts (Senecal & Nantel, 2004). Still, there are many questions that remain unanswered, such as how and why a recommendation system influences users' selections and whether the influence leads user to better decisions.

### **2.3.3 User Interfaces for Social Navigation and the Efficacy of Social Navigation Systems**

Given the popularity of social navigation systems, it is surprising that there is relatively little research regarding the effectiveness of various user interfaces for presenting community data and the overall efficacy of social navigation systems. These topics are closely connected and often overlap, and hence I discuss them together. Much of the research discussed concerns recommender systems because they are the dominant type of social navigation system; nonetheless, the research is applicable to other systems as well.

Recommender system researchers have argued that focusing on users and user interfaces is a promising area for improving recommendation systems (Herlocker et al., 2004; McNee, Kapoor et al., 2006). Early work in recommender system interfaces found that explaining recommendations from recommender systems increased user acceptance and may aid decision making (Herlocker, Konstan, &

Riedl, 2000). Another investigation of recommender systems studied how a user interface impacted user input to a social navigation system and found that (a) rating systems did not change users' ratings for items and (b) showing the system's recommended rating for items did influence users' ratings. The authors argued that this latter finding is the result of social conformity (Cosley et al., 2003).

Recent research by (McNee, Riedl et al., 2006b) has yielded a Human-Recommender Interaction (HRI) framework; this framework provides a taxonomy for understanding users of recommender systems, their goals, and their tasks; a contribution of this work is the proposed mapping from users to evaluation metrics, some of which are focused on the user interface. One outcome of this framework is the dependency between recommendation algorithm and user task: the efficacy of recommendation algorithms can be dependent on the tasks that a user is performing (McNee, Kapoor et al., 2006). The HRI framework hints at a fundamental question regarding social navigation: how effective are social navigation systems at helping users and how can systems' efficacy be measured and compared? This question has been largely overlooked in the evaluation of recommender systems (Herlocker et al., 2004).

One challenge in evaluating the efficacy of social navigation systems is that influence of others' action and behaviors is both a fundamental and tacit activity (Bandura, 1977)<sup>12</sup>. Because of these characteristics and likely many other factors, more time has been spent building and improving social navigation systems than understanding how users employ community data. This thesis endeavors to

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<sup>12</sup> Interestingly, this behavior is not uniquely human; many other animals gauge their behavior based on observations of others (Bennett & Giraldeau, 2001).

address this shortcoming in social navigation systems research. I define the social navigation user experience to be how users perceive, make sense of, and employ community data from social navigation systems. The goal of this thesis is to develop an understanding of the social navigation user experience and hence better understand the efficacy of social navigation systems.

There has limited effort to understand the social navigation user experience. As noted above, research shows that social navigation systems do exert influence on users, causing them to choose items at a higher rate than they otherwise would (Chen, 2008; Senecal & Nantel, 2004) and rate items more closely to the community's rating than they otherwise would (Cosley et al., 2003). It is unclear why social navigation systems exert influence over users' decisions and whether this influence is desirable. Another study of a social navigation system found that users can search the Internet more quickly using a social navigation system than they otherwise could, but it is unclear how a system confers this benefit (Wexelblat & Maes, 1999). A subjective assessment of a social navigation system found that users enjoy the social affordances of a social navigation system, such as seeing what others are doing and knowing that other people are present (Svensson et al., 2001).

Clearly, then, *two final challenges in employing a user-centered perspective for social navigation are (1) understanding the social navigation user experience and (2) measuring the efficacy of social navigation systems.*

## **2.4 Challenges in Employing a User-Centered Perspective for Social Navigation Systems**

I have argued that there are three challenges that arise from a user-centered perspective on social navigation systems:

1. creating systems that support the canonical activity in social navigation, decision making;
2. understanding the social navigation user experience—how users perceive, make sense of, and employ community data;
3. evaluating the efficacy of social navigation systems.

## **CHAPTER 3**

### **HERDING IN SOCIAL NAVIGATION SYTEMS: A WINDOW INTO THE SOCIAL NAVIGATION USER EXPERIENCE**

Chapter 2 identifies a shortcoming in social navigation systems research: there is limited research of the social navigation user experience. Given this dearth of research, it is surprising that there are many observations of herding behavior in social navigation systems (Cosley et al., 2003; Goecks & Mynatt, 2005b; Lampe & Resnick, 2004; Salganik et al., 2006; Svensson et al., 2001). When an individual engages in herd behavior, he makes a decision that is the same as the community consensus.

Herding is a useful probe for better understanding the social navigation for a variety of reasons. Herding is a striking finding, whether it occurs in a physical or digital space, and as such herding prompts reflection on the social navigation user experience in order to better understand why herding might have happened. Herding also prompts reflection on the efficacy and utility of social navigation systems. Previous research of social navigation systems has argued that social navigation systems, by virtue of providing community data, are useful (Dieberger et al., 2000; Resnick et al., 1994). Herding calls this argument into question because herding in a social navigation system homogenizes the choices made by a community of users; in general, such strong homogeneity in choices may be problematic if the predominant choice is wrong or harmful to a large number number of users. Thus, in order to determine whether and when to mitigate herding, it is necessary to understand herding; in the process of understanding herding, there is the opportunity—and perhaps necessity—to investigate the social navigation user experience as well.

This chapter discusses instances of herding in social navigation systems and concludes with a set of questions that herding raises about the social navigation user experience and the efficacy of social navigation systems.

### **3.1 Herding in a Social Navigation System for an Online Food & Recipe Store**

Svensson et al. observed herding in Kalas, a social navigation system that helped users navigate an online food store (Svensson, Höök, & Cöster, 2005; Svensson et al., 2001). In addition to basic navigational and searching functionality, Kalas enabled social navigation in numerous ways. Users could rate recipes, obtain recommendations for recipes, see what recipes others have rated highly and which areas other users were spending time in, and talk with other users about recipes. In reflecting on usage data and user interviews for Kalas, Svensson et al. reported that was necessary “to watch out for the snowball effect where the social trails lead more and more users down a path they do not perceive valuable in the long run” (Svensson et al., 2001). The ‘snowball effect’ is an instance of herding, and the ‘social trails’ that they refer to are simple indicators that show what recipe areas others are visiting. Finally, Svensson et al. argue that herding may lead to suboptimal outcomes for users.

Svensson et al. argue that there are two approaches to mitigating herding. First, they argue for employing a recommendation system to provide more personalized recommendations; however, as discussed below, recommendation systems are also subject to herding. Second, they argue that segmenting users into groups such as chefs and friends will enable users to choose which group they follow. This approach requires overcoming unequal benefits of participation among different user groups and achieving critical mass for each group (Grudin, 1994). Both of these solutions advocate providing more information to users,

either in the form of recommendations that are more tuned to individual preferences or by indicating the group that produced the social trail.

### **3.2 Herding in Moderation of Online Discussion Forums**

Lampe and Resnick have studied community moderation in an online discussion forum (Lampe & Resnick, 2004). In the moderation system that they studied, individuals can increase or decrease a post's moderation score depending on its contribution, and users can filter forums based on moderation scores so that they read only posts that are moderated highly. Thus, community moderation serves as a form of social navigation.

Lampe and Resnick observed herding behavior in moderation activities, and herding can either increase or decrease a post's moderation score. Not surprisingly, corrections to herding are more likely to occur for messages with high visibility (i.e. messages incorrectly moderated high) than those with low visibility (i.e. messages incorrectly moderated low). Hence, "[herding] could result in buried treasures, comments that should have high scores but do not." As in other social navigation systems, then, herding can lead to undesirable outcomes.

### **3.3 Herding in a Recommender System**

Cosley et al. found evidence of herding in a recommender system (Cosley et al., 2003). Cosley et al. found that when users are asked to re-rank a movie and are also shown the recommender system's prediction for the movie, their rank tends toward the predicted rating. Because recommender system portray their predicted level of interest as community data and because users' re-rankings gravitate toward the community data, Cosley et al. argue that this finding is indicative of a recommender system exerting social influence on users. This is an important finding because it demonstrates that herding can occur irrespective of



the aggregation algorithm that a social navigation system employs. Thus, herding behavior is a challenge for social navigation systems that employ simple aggregation algorithms, such as counting, and for social navigation systems that use complex aggregation algorithms such as collaborative filtering (Resnick et al., 1994).

Cosley et al. also observed that users expressed dissatisfaction with poor predictions, and they argue that this is an indication that users recognize manipulated predictions—predictions that arise from users whose ratings are made in order to exert social influence—because they are poor. However, a contradiction arises in these results: even if users recognized poor or manipulated predictions, they nonetheless conformed to them. An alternative explanation is that users’ negative reaction to poor rankings is independent of their recognition of manipulated predictions.

I concur with Cosley et al.’s core finding—that herding is present in recommendation systems—but argue that there is much more to be learned why social navigation systems cause herding.

### **3.4 Herding on the Internet and the World Wide Web**

The World Wide Web (WWW) is an interconnected hyperlink network with a primary purpose of sharing information; hence, it is reasonable to argue that the WWW is a slow, messy social navigation system. There is ample evidence to indicate that herding frequently arises in the WWW hyperlink network. A telltale indicator of herding in (semi-) random networks is a power-law distribution (Watts, 2002). In power law distributions, the most popular items are exponentially more popular than other items—even other items that are just a little less popular (Newman, 2005). Because the WWW is a semi-random network, power-law distributions provide evidence of herding. The connection

between power laws and herding is straightforward: items often become exponentially popular not because their inherent qualities make them exponentially more desirable but because cascades markedly increase an item's popularity.

The WWW's hyperlink, growth, and traffic all obey power law distributions (Adamic & Huberman, 2000; Huberman, 2001; Huberman & Adamic, 1999). For example, the number of hyperlinks to the  $N$ th most popular website is only about  $1/N$  the number of hyperlinks to the most popular website. Because search engines use the number of links to a website as a ranking mechanism (Page et al., 1998), the expectation is that the most popular websites for a topic often maintain and grow their popularity. Of course, growing popularity leads to more hyperlinks to the website, and herding that arises from the website's popularity begets additional herding. Even among groups of bloggers, hyperlink popularity frequently obeys a power law distribution and is likely fueled by herding (Kumar, Novak, Raghaven, & Tomkins, 2003). Finally, there is also evidence that the distribution of edits to Wikipedia articles obeys a power law distribution and a contributing factor of edit distribution is the visibility of articles (Wilkinson & Huberman, 2007); this evidence suggests that Wikipedia edits are subject to herding as well.

### **3.5 Herding on a Music Download Site**

Salganik et al. have found that herding within a social navigation system profoundly impacts the popularity of songs on a music download site (Salganik et al., 2006). Salganik et al. studied download rates of songs across multiple music download sites. There were three categories of sites: (a) a control site with no social navigation system; (b) a site with a simple social navigation system that showed download counts for songs but did not sort songs based on download

counts; and (c) a site that organized songs by download count. Each site was populated with the same songs.

This research yielded two principal findings. First, the presence of a social navigation system increased the inequality and unpredictability of songs' popularity. Salganik et al. measured inequality by the number of downloads; when a social navigation system was available, users downloaded highly popular songs more often than in the control condition and downloaded less popular songs less often. This finding is similar to the power law distribution that arises from the social navigation system that is the WWW: a social navigation system increases the inequality between items.

Salganik et al. also found that social navigation systems increased the unpredictability of songs' popularity. All sites that employed social navigation listed the number of downloads next to a song; however, some sites ordered songs based on the number of times they had been downloaded, and other sites randomly ordered the songs. Salganik et al. consider song ordering by popularity to be a stronger form of social navigation, and they found that increasing the presence of social navigation corresponded to increased unpredictability of a song's popularity.

Salganik et al. argue that these findings demonstrate that (1) social navigation systems exert social influence (Bond & Smith, 1996) on users and (2) social influence from social navigation systems yields unpredictable and suboptimal results. When a social navigation system is available, a song's quality is only a partial indicator of its success. The other indicator of success is the dynamic interactions among users' behavior and the social navigation system that aggregates and displays that behavior.

### 3.6 Summary

The following points summarize the observations of herding in social navigation systems:

- Herding occurs in multiple types of social navigation systems—including systems that simply aggregate and present user activity and those that employ user ratings to perform complex collaborative filtering—and in multiple domains. Herding, then, is likely a general phenomenon of social navigation systems and not an artifact that arises from particular systems or system features.
- There is a close connection between individual behavior—which is a key facet of the social navigation user experience—and group behavior in herding, and numerous analyses suggest that social influence at the individual level leads to herding at the group level. In general, then, it is useful to consider both individual and group behavior in social navigation systems and how they impact each other.
- Herding often leads to undesirable behaviors and outcomes. Herding can lead users astray and down paths that are not useful. Herding can also skew community data from a social navigation system and make it inaccurate, and this can lead users to make misinformed decisions. Finally, herding can lead to inequality and unpredictability amongst a set of items and can prevent high-quality items from becoming popular.
- Several social navigation system researchers posit that providing additional information to users, such as user groups or expertise among users, can mitigate herding. These ideas are largely untested; moreover, there is evidence that increasing the unanimity of community data can in fact lead to more herding.

Based on these observations, these questions about herding arise:

- What are the mechanisms and conditions that undergird herding in social navigation systems?
- What connections can be made between individual behavior, the social navigation user experience, and group behavior in social navigation systems?
- Under what conditions does herding occur in social navigation systems? And when does herding in social navigation systems lead to undesirable behaviors and outcomes?
- How can herding be mitigated in social navigation systems and what are the potential costs of such mitigation?

## **CHAPTER 4**

### **A THEORETICAL FOUNDATION FOR UNDERSTANDING THE SOCIAL NAVIGATION USER EXPERIENCE**

A large and significant body of research on computer-mediated human behavior shows that core tenets of behavioral and social science research hold true in computer-mediated environments [e.g. (Cosley, 2006; Reeves & Nass, 1996)]. This is unsurprising as it is unlikely that interactive computing has altered human behavior fundamentals. Given the relatively static nature of human behavior, it is likely fruitful to develop a foundation for understanding the social navigation user experience from research in other disciplines that has investigated behavior related to social navigation. Specifically, this chapter argues that social navigation is largely an online manifestation of numerous well-studied offline behaviors.

Nonetheless, interactive computing has and continues to have a significant impact on human behavior. Interactive computation affords new and more powerful applications of socially-guided behavior. Traditionally, physical or temporal constraints limit the transmission of social data, but interactive computing can obviate many such constraints. Computation simplifies and provides flexibility in all facets of social information usage, from collection to aggregation to display. Hence, the potential applications of social navigation in interactive computing are expansive, and it is important to appreciate and enhance the subtleties of social navigation in different domains.

Recall that this thesis defines the social navigation user experience to be how users perceive, make sense of, and employ community data from social navigation systems. To develop a theoretical foundation for understanding the social navigation user experience, it is useful to build upon psychological and economic research rather than start from scratch. Psychology and economics have produced much research documenting and understanding how individuals engage in *socially-aided decision making*. Decision making is a core perspective in my approach to understanding the user experience of social navigation, and hence these disciplines provide useful foundational elements upon which to develop a theoretical understanding of the social navigation user experience.

This chapter discusses three areas of research that undergird the social navigation user experience: psychological research of social influence, psychological research of advice taking and giving, and economic research of informational cascades. A synthesis of these bodies of research with the research in social navigation systems yields five hypotheses about the social navigation user experience. These hypotheses summarize the output from this theory-building process and afford evaluation of the process.

#### **4.1 Psychological Research of Social Influence**

Psychologists have studied how social data—what other people are saying and doing—can influence an individual’s decisions. In a classic study by Solomon Asch, individuals were asked to make straightforward, perceptual judgments about the lengths of lines. However, before making their judgment, each individual watched other people, who were—unbeknownst to the individual—confederates in the experiment, make numerous incorrect judgments. In this experiment, subjects answered incorrectly about 30% of the time (Asch, 1951). These findings suggest that individuals are strongly influenced by others’

decisions, and that this influence leads individuals to make a choice that agrees with the community consensus. Psychologists have labeled these behaviors, saying that *social influence* leads to *conformity*.

Subsequent research suggests a more nuanced portrait of social influence. A study by Deutsch and Gerard indicates that there are two types of social influence: normative and informational (Deutsch & Gerard, 1965). Normative influence occurs when individuals conform to the group opinion in order to avoid conflict or gain acceptance with others; this is the influence thought to be active in Asch's experiment. Informational influence occurs when individuals conform to the group because the individual employs the group opinion as a source of information. To demonstrate informational influence, Deutsch and Gerard showed that the less accurate an individual's information was, the more often he would conform. This result indicates that people were looking to see what decisions others had made, assuming those decisions were accurate, and using those decisions to guide their own decision.

Additional experiments measuring social influence provide insight into factors that impacts its strength. Bond and Smith performed a meta-analysis of studies using Ashe's line judgment task and, among other findings, determined that social influence decreases if individuals are making decisions in an individual area rather than in a room with other group members (Bond & Smith, 1996). Baron et al. documented interactions between social influence, incentives to answer correctly, and task difficulty in a study of eyewitness accuracy (as in the case of court testimony). This research yielded the following findings: (1) in general, increased incentives lead to greater social influence; (2) if a task is easy and incentives are high, social influence decreases and people conform less; and (3) if a task is difficult and incentives are high, social influence increases and people conform more. Taken together, these results indicate that, when



incentives are high, people are largely subject to informational influence; furthermore, difficult tasks can increase the effect of informational influence (Baron et al., 1996).

Consider social navigation in the context of social influence. Social navigation necessarily assumes some level of social influence; if users were not subject to social influence, there would be no reason for social navigation systems to provide community data. In fact, any social navigation system that augments a space and enables a user to see—before he acts—what actions or behaviors other people have taken is likely to generate social influence. It is, however, an open question whether social navigation is the product of normative influence or informational influence. Because either type of influence can result in social influence and social conformity, it is not clear which type of influence arises from social navigation systems.

Recall that Cosley et al. showed that recommendations from a social navigation system exert social influence on users, causing them to re-rate items more closely to the recommended rating than they had in the past (Cosley et al., 2003). However, this research did not attempt to determine the type of social influence the users are subject to. The type of social influence that a social navigation system exerts is quite important, as it impacts how a system might be improved to support usage of its community data.

Taken together, the characteristics of social influence and social navigation activities suggest that community data from a social navigation system exerts informational influence on users. When users employ community data, they are actively engaged in information-seeking, and this engagement suggests that there is motivation—and thus personal incentives—to make a correct decision. Moreover, individuals employ community data anonymously and individually

rather than in a group setting. Based on these factors and the research discussed previously, I posit the following:

***Hypothesis 1:*** *Community data from a social navigation system exerts informational influence on users.*

## **4.2 Giving, Accepting and Using Advice**

A second body of psychological research that contributes to understanding the social navigation user experience is that of giving, accepting, and using advice. The general experimental setup for advice-taking experiments involves a decision maker and an advisor (Bonaccio & Dalal, 2006). The first step is for both a subject and an advisor to read about a decision and then make an initial guess. Next, the advisor's guess is provided to the subject, and the subject is asked to make a final guess based on his initial guess and the advisor's guess. The accuracy of the subject's final decision is the dependent variable in advice-taking experiments.

Advice-taking experiments have numerous potential independent variables. An advisor will sometimes estimate the accuracy of his guess (e.g. 85%), and this estimate will be provided to the subject along with the advisor's guess. Subjects may also be asked to refine their guesses across multiple iterations using multiple advisors' guesses. Other variables employed in advice-taking experiments include expertise levels, incentives, and task type. This experimental structure is similar to social navigation: a user employs community data, a form of advice, to make a decision.

Individuals seek and accept advice for three reasons (Yaniv, 2004b). Firstly, a decision maker can often improve judgments and decision-making by accepting advice. The other two reasons for accepting advice are driven by social and societal motivations: accepting advice can help a decision maker justify her

decision, and accepting advice can serve to diffuse responsibility from the decision maker. Depending on context, these latter two motivations for accepting advice can either increase or decrease the accuracy of a decision.

There are several significant findings from psychological studies of advice taking that are relevant to social navigation (Bonaccio & Dalal, 2006; Yaniv, 2004a). First, individuals improve their accuracy considerably by using advice during estimation tasks, such as when famous historical events occurred. Experimental data suggests that as few as 3-6 semi-independent opinions can improve an individual's decision. Second, the implicit weighting that individuals employed to integrate opinions demonstrated two interesting features. First, individuals engage in ego-centric discounting, weighting their opinion more substantially than others' opinions (the average self-other weighting system is 70%-30%). Second, individuals discount opinions based on their distance from their own opinion, and opinions very far from an individual's opinion are discounted completely. These findings provide support for the intuition that seeking others' advice is a useful practice and perhaps could be further improved by mitigating ego-centric discounting.

I discuss the application of advice-taking research to the social navigation user experience in greater detail below. Nonetheless, this discussion of advice-taking and its relationship to social influence and social influence is sufficient to hypothesize that ego-centric discounting—one of the most robust findings in advice-taking research (Bonaccio & Dalal, 2006)—applies to the social navigation user experience as well:

***Hypothesis 2:*** *Individuals perform ego-centric discounting on community data from a social navigation system.*

### **4.3 Comparing Social Influence and Advice Taking**

It is instructive to compare the bodies of social influence research and advice-taking research and their application to social navigation systems. There are thorough overviews of social influence research (Bond & Smith, 1996) and advice-taking research available (Bonaccio & Dalal, 2006; Yaniv, 2004b). I use the term “social data” denotes the data that an individual can observe about others decisions or action; in social influence experiments, social data is the collection of decisions that others have made, and social data is advice-taking experiments is the advice provided to an individual.

Social influence research and advice-taking research share many similarities. To begin, these bodies both show that individuals often look to others’ decision, behaviors, or opinions when making decisions, and this activity impacts their decisions. There are also parallels between the two types of social influence and the three reasons that individuals accept advice. Informational social influence is similar to and likely drives the acceptance of advice to improve a decision’s accuracy. Normative influence likely drives the acceptance of advice to justify a decision and diffuse responsibility, although there are likely to be elements of informational influence as well.

However, just as I have argued that normative influence is minimal in social navigation systems, I argue that users are unlikely to use community data to justify a decision or diffuse responsibility for a decision. Using community data to these ends requires that users’ decisions be made public and that they be held accountable for their decisions. Accountability arises from a social or community structure that prescribes accountability among individuals and roles in the structure. Today’s social navigation systems rarely exist within a social or community structure, and hence users typically answer only to themselves for

their decisions. This is another reason to hypothesize that community data from social navigation systems exerts informational influence rather than normative influence on users or, stated alternatively, that users employ community data to improve the accuracy of their decisions.

There are important differences between social influence research and advice-taking research as well. In general, social influence research considers simple decisions, simple contexts, and simple social data. Decisions in social influence research focus on a small number of discrete choices, and many decisions have only two choices. Moreover, decisions in social influence research are made immediately rather than contemplated and made at later time. Lastly, social influence research typically does not ascribe any particular attributes, such as expertise or authority, to the people that are generating the social data.

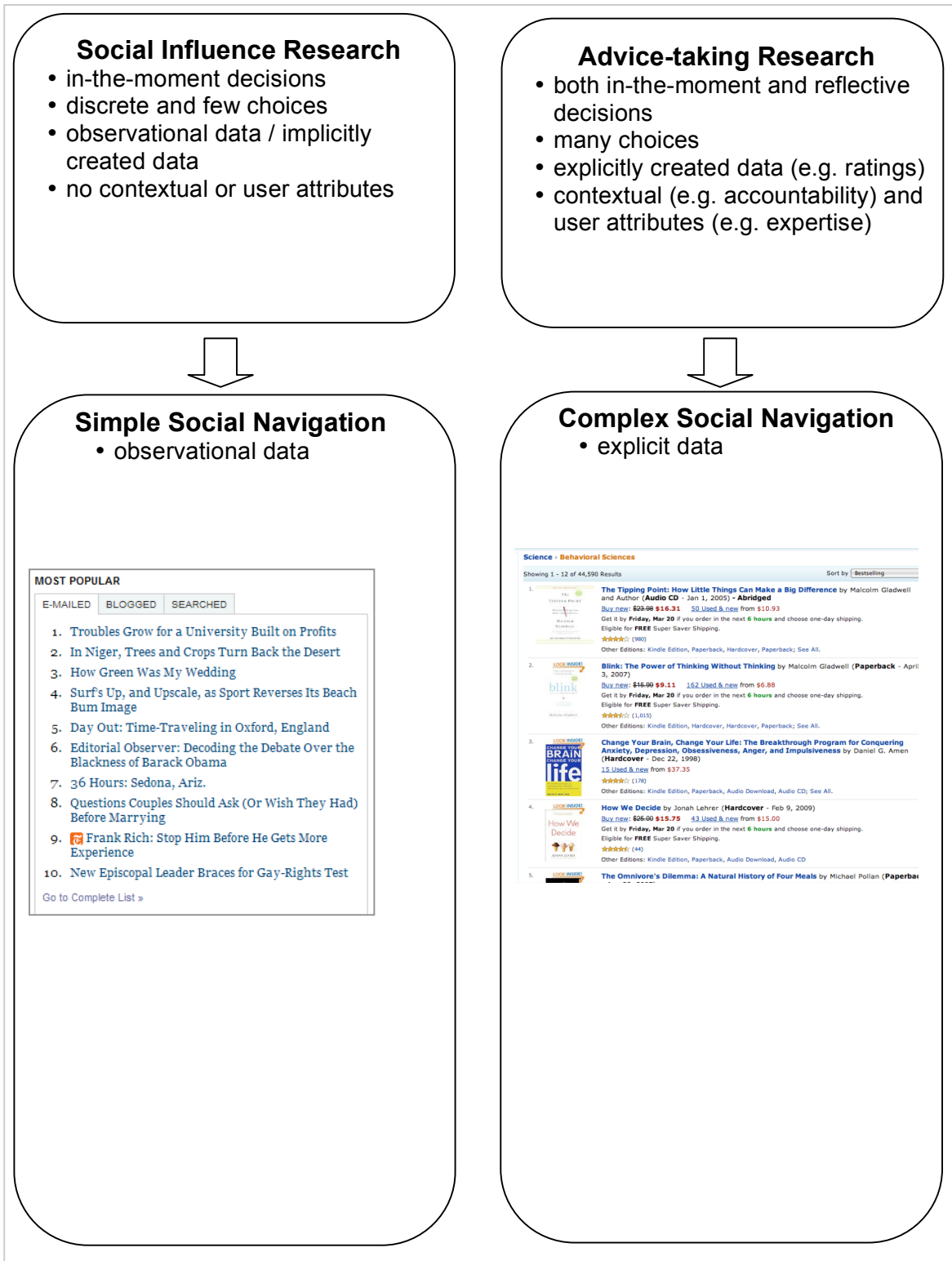
In contrast, advice-taking research focus on more complex decision making tasks. The decisions studied in advice-taking research are often continuous, such as approximating a percentage of wealth to put into a particular investment opportunity; these are also decisions in which individuals are able to reflect for a period of time before making a decision. Finally, advice-taking research has explored how people incorporate social data obtained from others with either expertise or authority and how these attributes impact the use of the social data.

Just as decisions can be simple or complex depending on various factors, social navigation systems can also be labeled as simple or complex. Social navigation systems that collect and display implicit activity data and weight all users' data equally can be considered simple, while social navigation systems that collect and display explicit activity data along with user attributes are more complex. For example, a simple social navigation system can produce a list of the most read or purchased books. A complex social navigation system might allow users to write

book reviews and enable others to rate reviewers and can produce a list of filtered reviews.

I purposely utilize the same adjectives—*simple* and *complex*—to differentiate between social influence research and advice-taking research as I do for describing the differences between social navigation systems in order to draw parallels amongst the comparisons. Social influence research studies simple decisions that are most often supported by simple social navigation systems. In contrast, advice-taking research studies more complex decisions, and these decisions are more often supported by complex social navigation systems. Hence, it is likely that social influence is a useful framework for understanding how users employ community data from simple social navigation systems.

It is less clear which framework is best employed to understand the social navigation user experience of a more complex social navigation system; both the social influence framework and the advice-taking framework likely can provide insight into usage of a more complex social navigation system. Figure 4.1 summarizes the application of psychological research toward the understanding of the social navigation user experience. Because I limit my focus in this thesis to simple social navigation systems that employ activity data, I do not derive any hypotheses for complex social navigation systems based on this discussion.



**Figure 4.1** Applying psychological frameworks to understand the social navigation user experience. Social influence research is useful for understanding simple social navigation, and advice-taking research is useful for understanding complex social navigation.

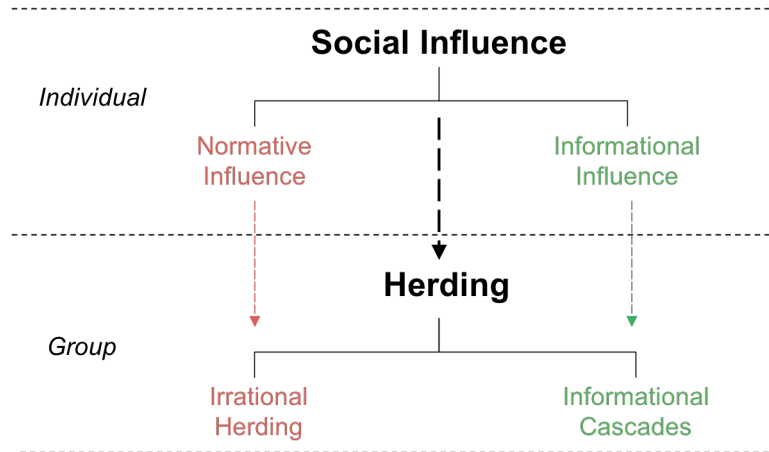
#### 4.4 Economic Research of Herding

Whereas psychological research of social influence and advice-taking focuses on individuals and their behavior, economic research of social influence focuses on groups and their behavior. Figure 4.2 shows my depiction of how the psychological research connects to the economic research. I claim that social influence at the individual level frequently leads to herding at the group level. Specifically, normative influence often leads to irrational herding, and informational influence often leads to *informational cascades* (Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992).

A classic informational cascade is a stock market bubble. Oftentimes a stock's price will continue to rise not because there is new information to suggest the stock's price should be higher but because each individual buyer infers that a stock's rising price is a signal that others believe a stock's price should be higher. Based on this logic, a buyer or planner then purchases the stock, increasing its price even higher and sending a (false) signal to others that he believes the stock should be priced even higher. A buyer or planner, then, observes what other people are doing (buying the stock), and decides to follow the crowd despite having either no information to justify his decision—or perhaps even information to the contrary (Devenow & Welch, 1996; Scharfstein & Stein, 1990). When many individuals employ this type of logic, a cascade can arise.

Informational cascades are a general socioeconomic phenomenon and are paradoxically named: they arise not from a plethora of information but *from a lack of information*. Informational cascades occur when individuals, acting in sequence and having observed the decisions of others before them, minimize or ignore their own information and make the same decision that the majority of others have made.





**Figure 4.2** Connecting social influence at the individual level to herding at the group level. Normative influence leads to irrational herding, and informational influence leads to informational cascades.

A close reading of informational cascades literature suggests that this body of research is founded on two chains of reasoning: (1) emotion drives normative influence, which in turn drives irrational herding and (2) rational thinking drives informational influence, which in turn drives informational cascades. Figure 4.2 illustrates the connection between types of social influence and types of herding. I focus on informational influence and informational cascades in this thesis, and as such I do not further discuss normative influence and irrational herding.

Surprisingly, individual behavior in a cascade is rational. An individual has two general sources of information: (1) private information—information available to him and (2) social data about what others are doing. When the information sources disagree, an individual should choose to follow the stronger information. Frequently, the stronger information arises from social data (Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992), and hence an individual frequently follows the social data despite contradictory private information.

However, from a collective perspective, this rational behavior becomes problematic. When an individual chooses to follow the community consensus rather than use his private information to make a decision, not only is his private

information lost but his decision also yields false information to subsequent decision makers. Subsequent decision makers, seeing others follow the consensus, infer that many people in the crowd have private information that led them to that decision, when in actuality, those individuals may be simply following the consensus. The inference an individual makes based on observed decisions of the crowd, then, can be quite inaccurate. Hence, an informational cascade arises because the crowd's signal is falsely strong and continually overwhelms the private information that individuals hold. Of course, if the crowd's decision is incorrect, then every subsequent person's decision will be incorrect.

Economists have studied the theory of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992) and the frequent, real-world occurrences of informational cascades in numerous domains, including financial markets (Devenow & Welch, 1996; Walden & Browne, 2002), nutritional recommendations (Taubes, 2007), fashions (Bikhchandani et al., 1992), information technology adoption (Walden & Browne, 2002), and website popularity (Huberman, 2001). Cascades occur at a surprisingly high rate. Theoretically, cascades occur at a rate of at least 12% if individuals' private information is 66% accurate (Bikhchandani et al., 1992). In experiments, cascades occurred about 80% of the time that they are theoretically possible (Anderson & Holt, 2006). Informational cascades are fragile because an individual or a small group with strong private information that contradicts the crowd's decision can often start a contradictory cascade quite easily via the same processes. Theory also suggests that the more people participating in a system, the more likely a cascade will occur (Bikhchandani et al., 1992).

Cascades do not necessarily lead to bad decisions. However, because it is not possible to predict in advance whether a cascade will lead to good or bad

decisions, it is often better to mitigate cascades because a cascade that leads to bad decisions can have significant negative consequences due to the speed and size with which cascades can propagate bad decisions.

There are three necessary conditions for cascades to (potentially) occur:

1. individuals make decision in sequence;
2. individuals can see what decisions others have made;
3. a discrete set of choices.

The first two criteria afford the opportunity for earlier decisions to influence later decisions, and the last criterion makes it difficult for an individual to make a decision that combines both his private information and the information he infers from others' decisions.

#### **4.4.1 Experiments of Informational Cascade Behavior**

Laboratory studies augment the theoretical research on informational cascades by demonstrating how human imperfections and motivations impact theoretical predictions (Anderson & Holt, 2006). Experimental studies of cascade behavior show that cascades do form, though not as quickly nor as frequently as theory predicts. Informational cascades form in about 80% of instances in which theory predicts a cascade would form. Errors in individual judgment slowed and sometimes prevented informational cascades from developing. Judgment errors occurred when there was little incentive for individuals to make correct decisions, near the beginning of a sequence when only a few people have made decisions (i.e. the crowd's signal was weak), when private information differs from the cascade choices, and when the inferred signal from the crowd and the signal from private information are contradictory and approximately equal strength (Anderson & Holt, 2006). A recent set of experiments investigated experimental

deviations in more detail. Results from one experiment indicate that, over long sequences of decisions and a large group, the equilibrium is a cycle of cascade formation, collapse, reformation, and so on; moreover, many cascades are eventually self-correcting (Goeree, Palfry, Rogers, & McKelvey, 2006).

A particularly interesting question is the degree to which individuals recognize and avoid cascades. Results from a recent study of information types indicate people acted in accordance with explicit advice more than implicit activity data even though both the advice and the activity data contained the same information (Celen et al., 2006). This research indicates that people are tacitly aware that activity data is less useful than explicit information. However, in another study where only activity data was available, individuals were often unable to recognize cascade behavior in others and thus unable to avoid participating in cascades (Grebe, Schmid, & Stiehler, 2008). Hence, the doubts that users have regarding activity data have little impact on their behavior when the only information available is activity data, and cascades are likely to be a common occurrence when only activity data is available.

The principal method that economists suggest for mitigating informational cascades is to promote independence among those making decisions, and promoting independence in decisions is accomplished by breaking any of the three necessary conditions for creating informational cascades. Thus, cascades can be prevented by compelling everyone to make decisions at once (instead of engaging in sequential decision making) or by hiding previous decisions from current decision makers (rather than enabling observation of previous decisions). Less effective but still useful in mitigating informational cascades is to provide individuals with a continuous set of choices so that individuals can more easily integrate and share information inferred from the crowd with their private information.

#### **4.4.2 An Informational Cascades Perspective on Social Navigation**

Informational cascades arise because observing others is an imperfect form of information gathering. Obtaining information from others' actions or decisions involves two basic steps:

1. observe others' behavior and actions to gather data;
2. make inferences to transform the observed data into useful information.

Social navigation systems make step 1 easier but do little to help users perform step 2. Step 2, however, lies at the heart of informational cascades: individuals have difficulty inferring information from observations, especially when inferring information based on observations of a crowd of people rather than a single person. Hence, it is reasonable to expect that informational cascades occur in social navigation systems.

To be precise, discussion throughout this chapter and in Chapter 3 provides ample reason to hypothesize that the herding in social navigation systems can be characterized as informational cascades. I have argued that informational influence is the main type of social influence that social navigation systems exert and that informational influence leads to informational cascades. Thus, I anticipate that cascades will occur in social navigation systems due to the informational influence that the system exerts. Also, social navigation systems meet these three criteria for informational cascades. Social navigation systems afford sequential decision-making. By definition, social navigation systems enable users to see what decisions others have previously made. Finally, social navigation systems nearly always offer a discrete set of choices, such as a set of hyperlinks or items to choose from.

In fact, social navigation systems not only meet the criteria for cascades but take them to their logical end. A social navigation system allows for unbounded sequential decision making because the system records and aggregates data

precisely and instantaneously. A social navigation system readily aggregates and displays *all* community data because that is the purpose of the system. Lastly, social navigation systems necessarily provide limited, discrete choices because only then can the system aggregate choices meaningfully (i.e. if there are too many choices, it may not be possible to aggregate decisions or may not be useful).

Given the sum of this evidence, I argue for a third hypothesis:

***Hypothesis 3:*** *Herding behavior in social navigation systems can be characterized as informational cascades.*

#### **4.5 The Size and Unanimity of Community Data**

Each of the three bodies of research discussed in this chapter has also demonstrated that the size and unanimity of a community's decisions can impact how a community's decisions impact individual decisions. See Bond and Smith (1996) for a discussion of size and unanimity's impact on social influence, Bonaccio and Dahal (2006) for a similar discussion focused on advice-taking, and Holt and Anderson (2006) for a discussion centered on informational cascades.

In general, size has been shown to have a minimal correlation with the strength that a community's decisions exert on individual decisions, but unanimity has been shown to have a much stronger impact, especially in social influence experiments. Hence, two additional hypotheses about the social navigation user experience posit that the size and unanimity of community data correlate with the strength of the influence that the community data exerts on individual decisions:

***Hypothesis 4:*** *The size of the group that the community data represents directly correlates with the strength of the community data's social influence.*

***Hypothesis 5:*** *The unanimity of the group's consensus that the community data represents directly correlates with the strength of the community data's social influence.*

#### **4.6 Hypotheses about the Social Navigation User Experience**

I have developed a theoretical foundation for the social navigation user experience by synthesizing research in social navigation systems, social influence, advice-taking, and informational cascades. Three hypotheses summarize this foundation:

***Hypothesis 1:*** *Community data from a social navigation system exerts informational influence on users.*

***Hypothesis 2:*** *Individuals perform ego-centric discounting on community data from a social navigation system.*

***Hypothesis 3:*** *Herding behavior in social navigation systems can be characterized as informational cascades.*

***Hypothesis 4:*** *The size of the group that the community data represents directly correlates with the strength of the community data's social influence.*

***Hypothesis 5:*** *The unanimity of the group's consensus that the community data represents directly correlates with the strength of the community data's social influence.*

## **CHAPTER 5**

### **SOCIAL NAVIGATION FOR END-USER PRIVACY AND SECURITY MANAGEMENT**

Social navigation is a promising approach for supporting end-user privacy and security management. Since many users are unmotivated to manage their privacy and security (Dourish, Grinter, Delgado de la Flor, & Joseph, 2004; Whitten & Tygar, 1999) and do not understand the technical issues associated with privacy and security management (Gross & Rosson, 2007; Schneier, 2004), social navigation systems can provide a new, simpler approach to informed decision making. For example, since prior research has shown that users often prefer to delegate privacy and security management to others (Dourish et al., 2004), social navigation can provide for such delegation: a user that is unsure about how to manage his privacy or security can simply choose to follow the community's majority decision.

This chapter describes two prototype systems that explore how social navigation can be employed to help users manage their privacy and security. The Acumen system employs social navigation for privacy management; Acumen helps individuals manage their Internet cookies both manually and automatically based on the behavior of others. The Bonfire system uses social navigation for security management; Bonfire is a personal firewall that uses multiple types of social navigation data to help users make firewall management decisions.

Observations from Acumen and Bonfire suggest that, despite the promise of social navigation in security and privacy applications, there are significant challenges in applying the technique in these domains. In particular, due to the



types of decisions and general lack of expertise among users in these domains, individuals may make incorrect inferences from a social navigation system's community data and misuse community data when making decisions. These incorrect inferences and misuse of community data can lead to even incorrect individuals decisions, inaccurate community data, and herding behavior in which a community consensus builds for an incorrect decision.

These challenges serve as the motivation for this chapter. These challenges are the result of *informational cascades* that can arise in these systems. Recall that informational cascades occur when individuals, faced with a decision, ignore their own information and choose to go with the majority decision, thereby creating a herd or cascade (Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992). An analysis of Acumen and Bonfire indicates that mitigating informational cascades is necessary if social navigation systems are to be useful for privacy and security management.

This chapter is based on research described in (Goecks & Mynatt, 2005a) and (Goecks, Edwards, & Mynatt, 2008).

## **5.1 Addressing End-User Privacy and Security Management with Social Navigation**

It is important to establish why social navigation might be useful for supporting end-user privacy and security management; this understanding provides the foundation for analyzing the efficacy of social navigation systems applied to privacy and security management. In this thesis, the term “end-users” denotes users that have no special or explicit training in managing their privacy or security.

There are similarities in how users think about privacy management and security management. Previous research argues that people perceive privacy

management to be a boundary management process, and potential privacy boundaries include temporal, interpersonal, and boundaries between a private and public sphere (Palen & Dourish, 2003). Similarly, there is evidence that users perceive security as a barrier which should “keep things out,” regardless of whether those things are privacy threats or security threats, and that controlling and configuring this barrier is a key activity in security management (Anton, Earp, Potts, & Alspaugh, 2001; Dourish et al., 2004).

In general, when a user manages a boundary for the purposes of meeting privacy or security needs, she is making decisions about where to place the boundary, what can cross the boundary, and when to change the boundary to meet current context and constraints. While this is a very general description of boundary management, there is one commonality among most boundary management activities: decision making—both implicit and explicit—is the core activity of boundary management. It is unreasonable to attempt to automate all privacy and security management decisions due to numerous technical and social factors that limit the efficacy and acceptance of such automation (Edwards, Poole, & Stoll, 2007). Thus it is important to explore solutions that help users make good decisions when managing their privacy and security.

This research, then, focuses on the decision-making processes that users engage in when performing the boundary management activities associated with meeting their privacy or security needs. Thus, references to privacy and security management refer to the decisions that users must make to create, adjust, and update their privacy and security settings. Furthermore, a particular area of focus is the challenges that users face when making these decisions and how social navigation can address these challenges.

There are two common issues that end-users face when making privacy and security management decisions. First, end users often do not understand the technical issues associated with privacy and security management and, lacking this understanding, users cannot make informed decisions (Schneier, 2004). For instance, when managing a personal firewall, users often must understand what a process is, what a port is, and what it means to block a process or port from accessing the Internet. In addition, abstractions, such as access policies, are common in computer security but problematic for end users (Whitten & Tygar, 1999), and privacy management is frequently confounded by complex settings [e.g. (Millett, B., & Felten, 2001)].

Another barrier for effective end-user privacy and security management is motivation. Most users are uninterested in the technical details of computer security (Gross & Rosson, 2007) and lack the incentives and time to effectively manage their security (Dourish et al., 2004). A main reason for users' low motivation is that security is frequently a complementary task, performed alongside or in conjunction with a primary task (Whitten & Tygar, 1999).

Low motivation to engage in privacy and security management activities leads users to engage in particular behaviors. First, users often seek to spend as little time as possible on security and thus make security decisions quickly, do not experiment with security settings, and do not revisit past security decisions (Herzog & Shahmehri, 2007b). Second, many users try to delegate privacy and security management to other people (Dourish et al., 2004). In many instances, however, users may struggle to find delegates because expertise in privacy and security management is rare.

### **5.1.1 Matching Social Navigation to End-user Security and Privacy Management**

Social navigation has the potential to address the common problems in end-user privacy and security. Recall that social navigation systems enable a user to see what other people have been doing or saying by automatically capturing, aggregating, and displaying the behavior and activities of its community of users (Dourish & Chalmers, 1994). For example, a social navigation system might provide “paths” based on previous user behavior that lead to the most highly rated posts in a discussion forum, the most frequently downloaded food recipes from an online cookbook, recommendations for songs that a user might be interested in purchasing from a music store, or—in the case of Dourish and Chalmers’ original work—navigation of information spaces based on social activity rather than spatial markers (Dourish & Chalmers, 1994).

Recall that one challenge users face when making decisions to manage their privacy or security is understanding the technical issues associated with a decision. Using social navigation systems to support privacy and security management means that users have an additional source of data in the system’s community data, and this data may be easier to understand and use than the technical data typically associated with privacy and security decisions (Herzog & Shahmehri, 2007b). Also, people often are able to learn quickly by observing others (Bandura, 1977), and social navigation supports this type of learning as well.

The other principal challenge in privacy and security management is low motivation among users and their preference for delegating privacy and security management (Dourish et al., 2004); social navigation can address this challenge as well. A simple social navigation system that collects and displays a

community's actions and decisions imposes minimal burden on users, and thus individuals can participate and use a social navigation system with nominal effort. Social navigation systems provides a way for users to delegate their decisions to others: a user that is unsure of how to manage his privacy or security can simply choose to follow the community's majority decision.

Finally, preliminary research has analyzed how social navigation might be applied to end-user privacy and security management. An analysis of user help techniques for end-user security applications suggests that social navigation is amongst the most natural and straightforward forms of help and learning, though it does requires interpretation of community data (Herzog & Shahmehri, 2007b). DiGioia and Dourish recently discussed how social navigation might help users understand patterns of conventional use and the activities of others (DiGioia & Dourish, 2005). This chapter describes research that builds on this work, taking significant steps to understand how social navigation helps users make decisions to manage their privacy or security and what challenges arise from using social navigation in these domains.

## **5.2 Supporting End-User Privacy Management with Social Navigation**

This section describes the application of social navigation to help users manage a common Internet privacy problem.

### **5.2.1 The Problem: Managing Web-browser Cookies**

A common privacy concern that Internet users have is the collection of personal data by third parties; users want the ability to control when, how, and what information they share with third parties (Jensen & Potts, 2005; Paine, Reips, Stieger, Joinson, & Buchanan, 2007). Internet cookies are particularly troublesome in this respect because websites can use cookies to collect and store information about users; sites often use cookies to monitor users' browsing

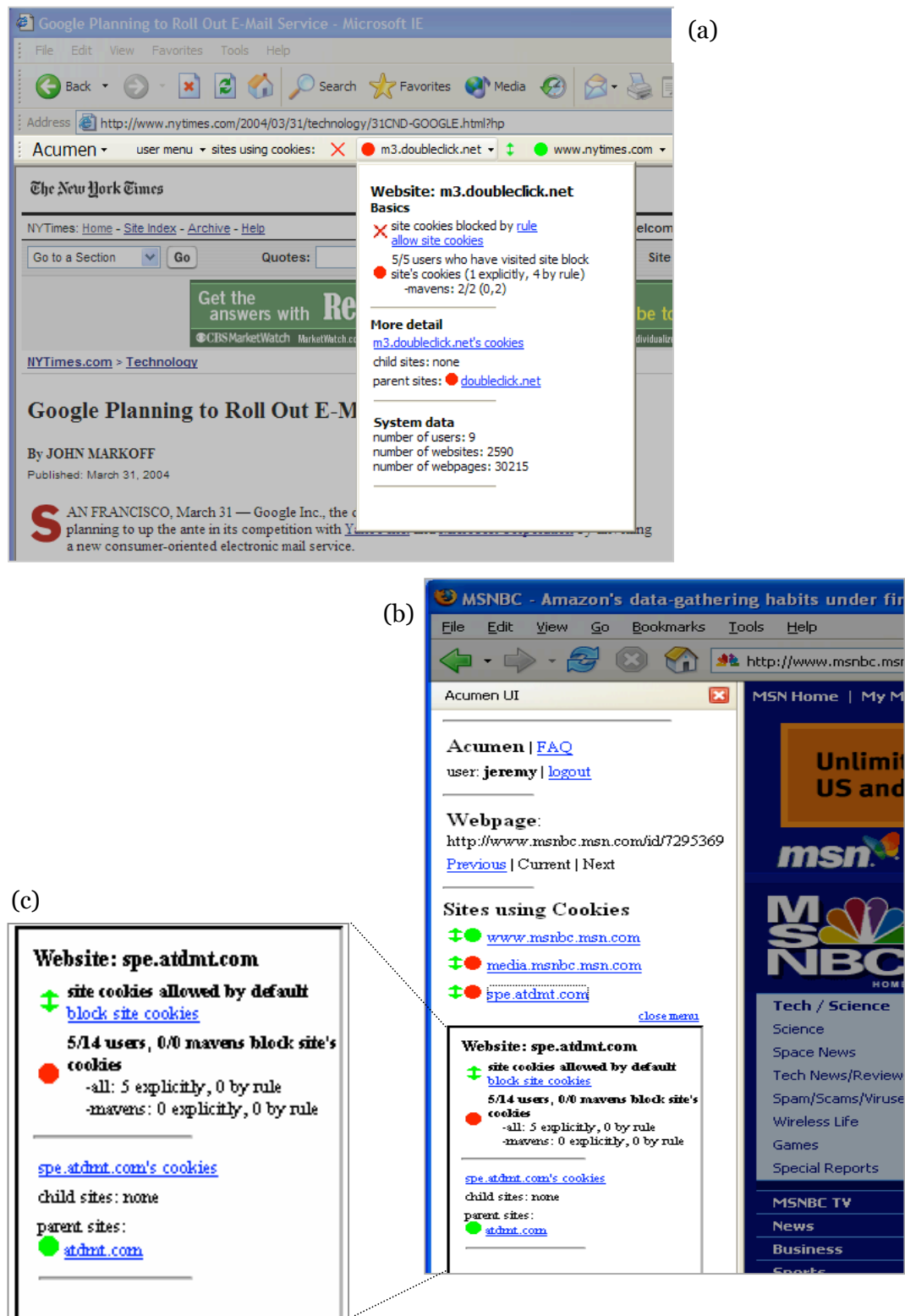
activities. In fact, at least thirty-five percent of websites use cookies to collect such information (Federal Trade Commission, 2000).

Much work has been done to help users manage their cookies. Many online privacy policies describe how a website uses cookies and what data they collect using them, but online privacy policies are often difficult to locate and understand (Jensen & Potts, 2004). The Platform for Privacy Preferences (P3P) specification enables websites to encode a privacy policy in a machine-readable format; software agents can then interpret and utilize P3P policies (Cranor, 2002). P3P, however, has not simplified web browser or cookie privacy settings.

Both of today's major browsers, Internet Explorer and Firefox, provide users with the ability to manage cookies in various ways. However, studies of past versions of these browsers show that there are problems and inadequacies with both browsers' cookie management tools, such as making them hard to find and modify, providing little on-going awareness of cookies, and using terminology that users do not understand (Friedman, Howe, & Felten, 2002; Millett et al., 2001). Recent studies show that while awareness of cookies is growing, many users are not knowledgeable enough to manage cookies effectively (InsightExpress, 2007; Pew Internet & American Life Project, 2005).

### **5.2.2 Acumen**

The Acumen system (Goecks & Mynatt, 2005b) (Figure 5.1) helps users manage their web-browser cookies.



**Figure 5.1** Screenshots of the Acumen system. From top left clockwise: (a) the Acumen Internet Explorer toolbar on *The New York Times* website; (b) the Acumen Firefox Sidebar on the MSNBC website; and (c) detailed community data about a website's cookies from the Acumen Firefox Sidebar.

Acumen was developed using an iterative design process; six full iterations were completed. During each iteration, numerous interface prototypes were developed, and the most promising prototypes were presented to a mix of HCI practitioners, privacy experts, and everyday users to obtain feedback from them. Feedback was obtained from a mix of individuals in order to gather data from individuals with different levels of expertise and diverse perspectives. Practitioners and experts were quite important to the process because they provided insights that users did not, especially the potential problems that users might have in using Acumen's community data. Feedback obtained during each iteration was employed to refine and select techniques from both social navigation systems research and digital privacy management research for subsequent iterations.

Acumen integrates with a browser's standard cookie management functionality; users manage cookies at the website level, allowing or blocking cookies from websites. Acumen allows all cookies by default. As a user browses the web, Acumen provides information about the websites that are using cookies on the pages that he visits and community data for these websites. When a user visits a webpage, Acumen displays the websites using cookies on the page and next to each website, an icon that summarizes the community data for the website.

Acumen's community data consists of the number of users who have "visited" a website (i.e. requested a file from the site), the number of such users who allow the site's cookies, and the number of users who block the site's cookies. Collecting and displaying this simple form of community data has proven successful for promoting awareness and supporting decision making in the past (Hill et al., 1992; Svensson et al., 2001; Wexelblat & Maes, 1999). Acumen encodes its community data in a circle icon using colors established by the Privacy Bird



application (Cranor, 2002); using a colored icon as the primary indicator has been shown to be effective in providing information to users when they are making a privacy decision (Cranor, 2006).

Users can leverage Acumen's community data in multiple ways. Like the Privacy Bird, Acumen enables a user to maintain awareness of ongoing privacy actions and changes via a persistent, peripheral interface near the top of the web browser. Acumen's interface enables a user to maintain awareness of (a) the websites using cookies on the web pages that she is visiting and (b) whether other community members generally allow or block cookies from these sites. When making the decision to allow or block a website's cookies, users can view the site's community data in detail and use this information to inform their decision.

Users can also employ simple rules that leverage community data to automatically block cookies. Users can create rules of the form 'If X% of users have blocked cookies from a website, then automatically block the site's cookies.' Users choose a rule's threshold percentage when they create it. Using community data to automate actions is novel; the purpose of this feature is to help users more easily delegate cookie management to the community.

A concern that became prominent when designing Acumen is herding behavior (Banerjee, 1992). In herd behavior, individuals unsure of a decision often choose to follow the majority—the herd—causing the herd to grow, which then leads even more individuals to follow the herd. Herding behavior can continue via this cycle for a long time, and if users build a consensus for an incorrect decision, many users can be misled and thus choose the incorrect decision.

Herd behavior is especially likely in Acumen for two reasons. First, most users have little knowledge of cookie management and thus are likely to follow the majority decision. Secondly, herd behavior is likely because users cannot delay

making management decisions about cookies, even if there is very little community data to help them. When a user visits a webpage using cookies, he must choose whether to allow or block those cookies immediately, even if there is limited community data. Decisions made with less community data are often more prone to herding behavior because there is less information contained in the data (Banerjee, 1992).

In an effort to mitigate bad herding behavior—herding behavior that leads to poor, incorrect, or uninformed decisions—Acumen provides community data from a select subset of ‘experts.’ Acumen leverages experts’ knowledge by anonymously identifying and providing community data from them. Providing expert community data can help mitigate bad herding behavior and also promote good herding behavior by enabling uninformed users followed experts.

To identify experts, Acumen computes an ‘expert rating’ for each individual, based on a user’s breadth and depth of cookie management activity. Acumen labels users with the top 20% of ratings as experts and encodes the experts’ community data as a smaller circular icon embedded in the large community data icon. Embedding the experts’ data this way makes it easy for users to see the expert data and contrast it with the overall community data.

### **5.2.3 Lessons Learned from Acumen**

A limited, controlled deployment of Acumen was performed. Nine users used Acumen for six weeks, and the deployment’s goal was to obtain data about and develop a better understanding of the challenges encountered during Acumen’s design. At the end of the six weeks, Acumen’s database contained data for over 2650 websites; users had blocked cookies from 85 websites using Acumen. There are two lessons to be learned from Acumen’s design and deployment.

Firstly, Acumen was successful at helping users make good decisions for cookies with clear criteria. Acumen's users generally allowed 'good' cookies, which provided a high benefit with a low cost, and blocked 'bad' cookies, which provided little benefits but had a high cost. However, for cookies with a more complex or ambiguous benefit-cost ratio, Acumen proved less useful as users disagreed about whether to allow or block such cookies.

Another way to state this finding is that Acumen's community data proved useful for making objective decisions—decisions where personal preferences or biases were relatively unimportant in the decision-making process—and less useful for subjective decisions.

Secondly, in interviews, six of nine users indicated that they engaged in herding behavior and blocked a site's cookies because others had. It was difficult to determine whether experts' community data was useful in mitigating herd behavior due to the small number of users in the deployment. That said, three of nine users indicated that they were skeptical that experts were more knowledgeable than other users and chose to use community data from all users rather than experts' data.

### **5.3 Supporting End-user Security Management with Social Navigation**

This section describes how social navigation can be applied to address a classic end-user security management problem: personal firewall management.

#### **5.3.1 Personal Firewall Management**

A personal firewall is software that enables an individual to control the data flow between his computer and the Internet; typically, a user controls this data flow by granting or denying software applications on his computer access to the Internet. Personal firewalls are increasingly important because pervasive,

persistent, and high-bandwidth connections to the Internet are becoming common both in the home and in public (via wireless hotspots) (Horrigan, 2007; Pew Internet & American Life Project, 2006). More than half of all broadband users have installed a personal firewall (Pew Internet & American Life Project, 2004).

Persistent, high-bandwidth connections to the Internet pose numerous security and privacy risks to users. These connections make it easy for users to download, run, and accidentally share malicious software—such as software that attempts to obtain passwords or financial records for use in identity theft.

Data flow between a user's computer and the Internet also has privacy implications. For instance, there are applications that report information about an individual's activities back to web servers on the Internet, such as his web browsing activities<sup>13</sup> and whether he read an email message<sup>14</sup>. Finally, general annoyances also arise from data flow issues; popup windows from spyware often occur because the spyware is connecting to another computer on the Internet.

End users can significantly alleviate these problems by using a personal firewall effectively; effective use of firewalls means making good decisions about which programs are allowed connect to, send, and receive data from the Internet.

Unfortunately, using a personal firewall effectively is difficult because personal firewalls suffer from two significant end-user security management problems discussed earlier: (1) firewall management is a complementary activity to other primary activities, such as sending and receiving email, browsing the Internet, and updating software; and (2) firewall management often requires users to

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<sup>13</sup> <http://www.zango.com>

<sup>14</sup> <http://www.didtheyreadit.com>

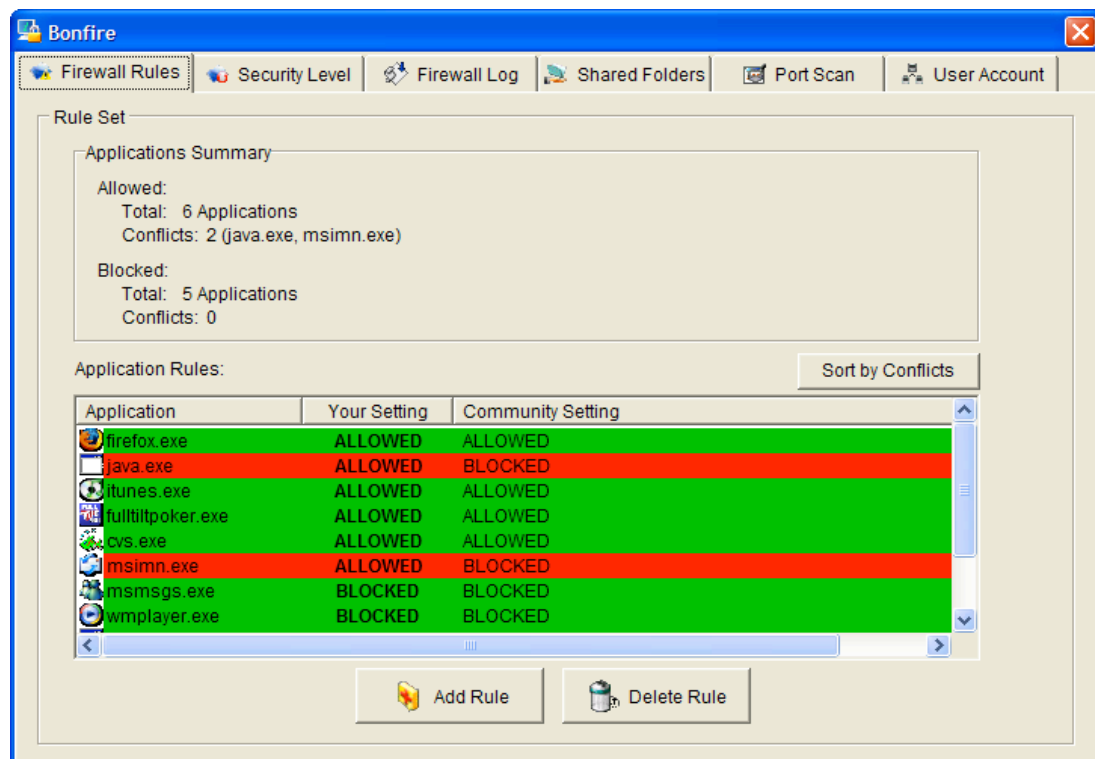
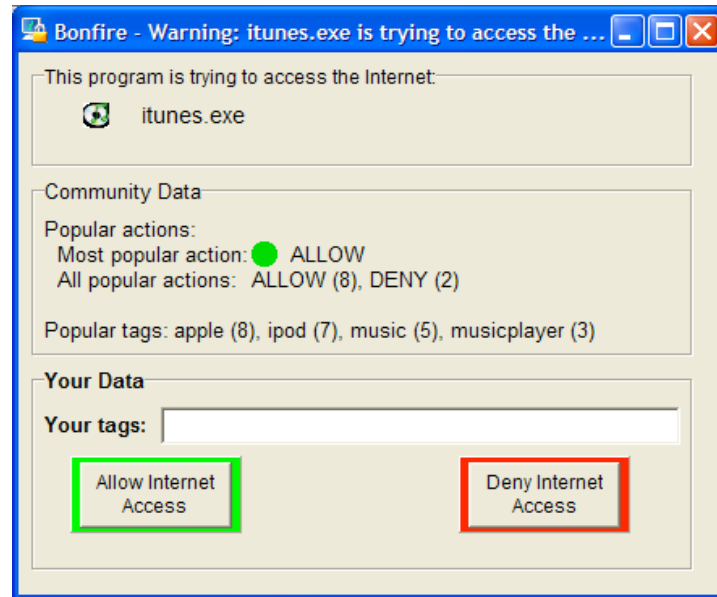
understand technical information—such as IP addresses, ports, and processes—in order to complete primary tasks (Herzog & Shahmehri, 2007a).

### **5.3.2 Bonfire**

Bonfire (Figure 5.2) is a personal firewall infused with a social navigation system. The goals for Bonfire were to explore (a) the application of social navigation to a new problem domain and (b) the mitigation of herding behavior using lessons learned from Acumen.

Bonfire was also developed using iterative design. Prototypes of Bonfire's interfaces were repeatedly developed and presented to HCI practitioners, security experts, and everyday users to get feedback; feedback was applied to refine and select techniques from the social navigation and security management bodies of research. A total of seven iterations were completed to create Bonfire.

Bonfire provides functionality comparable to other popular personal firewalls, notifying a user via a popup alert window (Figure 5.2, top) when a firewall management decision must be made. Bonfire notifies a user when a program on his computer attempts to access the Internet or tries to receive connections from Internet. Bonfire also provides a summary window (Figure 5.2, bottom) where users can view current rules, create new rules, and delete unwanted rules. Rules dictate the programs that can access the Internet and those that cannot.



**Figure 5.2:** Screenshots of the Bonfire system. Top: alert window that enables users to employ community data to make firewall management decisions; bottom: Bonfire's summary interface for viewing firewall decisions in relation to the community.

Bonfire's community data is organized around programs (e.g. itunes.exe, mysearchbar.exe); for a program, Bonfire records the number of users who have allowed a program Internet access and the number of users who have blocked the program's access. Bonfire uses this community data in multiple ways throughout its interfaces. Bonfire also enables users to employ tagging (Dourish et al., 2000; Shilad et al., 2006) as a supplementary community data source in Bonfire. Tagging is the practice of applying multiple, short words or phrases to describe an item; each word or phrase is an independent tag that describes the item.

Bonfire presents community data in a section of its alert window. At the top of this section is the most popular action that the community has taken when faced with this decision. This information is presented as text and via a colored circle that corresponds to the background color of the decision buttons at the bottom of the window. The purpose of this correspondence is to reinforce the connection between Bonfire's community data and the user's decision. Using a colored icon as the primary indicator, as Bonfire does for its community data, has been shown to be effective in providing information to users when they are making a security decision (Cranor, 2006).

Next, more details of Bonfire's community data are provided in the form of 'popular actions.' This is a list of frequent decisions that the community has made, and this information includes, in parentheses, the number of users that have made each decision. For some firewall decisions, there are more than two choices, hence use of label 'popular actions,' which can accommodate multiple options.

Finally, Bonfire shows the most popular tags that users have applied to the program. Tagging is a response to the herding behavior that occurred in Acumen and is likely to occur in Bonfire for the same reasons. Many users lack sufficient

technical knowledge to use firewalls (Herzog & Shahmehri, 2007a) and hence were likely follow the majority decision. In addition, there were likely to be instances in which users were faced with a firewall management decision and for which there was little community data, and herding towards incorrect decisions is more likely with relatively little data (Banerjee, 1992).

Promoting good herding behavior—herding behavior that led to correct decisions—in Acumen was quite challenging. Hence, Bonfire was designed to mitigate all herding, regardless of whether the herding is good or bad. Feedback on early iterations of Bonfire suggested that herding might be mitigated by providing additional information to supplement Bonfire’s existing community data, such as why others blocked a program’s Internet access or the context in which decisions were made.

For these reasons, tagging was used as an additional source of community data. Tagging occupies a “sweet spot” among community data types for a social navigation system. Tagging imposes a low burden on users, yet tags are relatively easy to understand and use. Tags are often used to facilitate searching and navigating, but tags are expected to play a different role in Bonfire. It is anticipated that Bonfire’s users will apply tags to a program to describe it or indicate why they blocked it. Bonfire’s community data types are intended to complement each other. Bonfire’s decision data summarizes the community’s actions, and the tagging data provides information about why those actions were taken.

In Bonfire’s alert window, tags that users have applied to a program are below the popular actions. As with popular actions, the number in parentheses next to a tag is the number of people who have applied the tag. Lastly, the alert window



provides a section for a user to input her own tags for the program and make a decision for this firewall management question.

Bonfire's summary window provides an overview of the application rules that a user has created and color-codes the rules to indicate whether the user's decisions agrees (green) or disagrees (red) with Bonfire's community data. This interface makes it easy for users to quickly identify which of their decisions differ from the community norm and revisit those decisions as needed.

### **5.3.3 Lessons Learned from Bonfire**

Unlike web-browser cookie management, personal firewall management is comprised mostly of *objective* decisions. That is, when users manage their firewalls, they are likely to manage them in similar ways; most users employ their firewall to block spyware, adware, and other malware, and users generally agree on what constitutes malware. While there are individual differences in firewall management (e.g. some users will open particular ports to play online multiplayer games), the majority of decisions that users encounter are objective. This is in contrast to the privacy domain targeted by Acumen, in which there are a variety of decision types—subjective decisions, rooted in users' own orientation toward privacy and their daily routines of site visitation, and objective decisions guided by the identification of certain sites as misusing cookies or posing a true risk to users' privacy.

Bonfire's design demonstrates a promising approach to mitigating herding behavior by combining activity-based community data—data about what other people are doing—and tagging. This approach provides insight into why herding behavior may occur: users may have difficulty interpreting and using solely activity-based community data to make privacy and security management decisions. Tagging provides a more explicit form of community data that

complements the decision-based community data by providing information about why users made decisions.

## **5.4 Reflections: Understanding Herding in Privacy and Security**

### **Managements**

Reflections prompted by Acumen and Bonfire suggest that the user experience of social navigation in end-user security and privacy management is *qualitatively different* than social navigation in other domains. These differences lead to herding behaviors that are especially damaging in the security and privacy contexts.

This section discusses the unique challenges that are inherent in the security and privacy domains themselves. These challenges are rooted in the distinction between subjective and objective domains and in the connection between the herding behavior seen in these domains and the theory of information cascades, which can serve as a lens through which to better understand social navigation and shed light on opportunities to mitigate herding.

Concisely, this argument states that when a user encounters an objective decision—as is the predominant decision-type in privacy and security management—he attempts to infer information from a social navigation system’s community data and uses the inferred information to make a decision. If not accounted for in a social navigation system’s design, use of a system’s community data as an inferential information source can lead to herding behavior and render the community data uninformative or even incorrect. Uninformative or incorrect community data then leads to numerous and potentially a great number of incorrect decisions.

### 5.4.1 Subjective vs. Objective Decisions

Traditionally, social navigation systems have been applied to domains such as music, movies, recipes, and books. In these domains, the system's goal is to help a user make decisions that lead to items that appeal to her; in other words, the perspective that matters in these domains is that of individual users. These domains are described as *taste-based* or *subjective domains* because the evaluation criterion is subjective.

In contrast, *objective*<sup>15</sup> *domains* are domains where users share evaluation criteria and thereby agree on a desirable answer or goal state. Often, however, the desirable answer or state is not known in advance. I am not aware of any social navigation systems that have been applied to largely objective domains, with the exception of the Acumen and Bonfire systems described here.

For instance, many firewall questions fall into an objective domain. Users agree that they do not want malware to connect to the Internet because the malware can do damage to their computers. All users, then, will choose to block a software program from accessing the Internet if it is known to be malware. In summary, users agree on an evaluation criterion—is the software malware?—and the desirable decision, blocking malware from accessing the Internet. The challenge for a social navigation system applied to firewall management, then, is helping users decide whether to block a new program that may be malware.

Very few domains are completely subjective or objective, but most domains have more objective decisions or more subjective decisions. For example, one

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<sup>15</sup> For this discussion, 'intersubjective' is perhaps a more precise term than 'objective' because 'intersubjective' denotes the sharing of subjective states amongst two or more individuals whereas 'objective' denotes the sharing of states amongst all individuals. However, I use the term 'objective' to draw a clear distinction between subjective and objective experiences, decisions, and domains.

might posit that domains with a strongly objective flavor might include finances (in which maximizing wealth is an objectively “better” decision), healthcare, and the privacy and security domains described in this paper.

An important difference between subjective and objective domains concerns how well users are able to make sense of the community data that a social navigation system provides.

In subjective domains, an individual can often readily understand the basis of community data and thus make inferences from the data. Community data in a subjective domain arises from user preferences. An individual viewing community data can be confident that (a) users know their personal preferences and (b) users are making decisions that reflect those preferences, such as buying a book or choosing a recipe that appeals to their interests. An individual viewing community data, then, can infer that users are making decisions with ample knowledge and acting according to that knowledge. These inferences are intuitive and allow an individual to use community data as an authentic information source when making decisions in subjective domains.

However, this logic frequently does not hold in privacy and security management. Managing one’s privacy and security can be complex, and users often have limited expertise in these domains. Unlike subjective domains, where it can be assumed that users know their personal preferences and act on them, it is problematic to assume that others have expertise in objective domains and that they are acting on their expertise because this assumption may be incorrect.

When using community data to make privacy and security management decisions, then, this lack of knowledge about others’ expertise makes it difficult for an individual to accurately infer information from community data and use the data as an authentic information source. This is a key difficulty in using

social navigation to support decision-making in privacy and security management.

#### **5.4.1 Informational Cascades in Acumen and Bonfire**

Lessons learned from Acumen and Bonfire indicate that many users welcome community data from a social navigation system to help them make privacy and security management decisions because they are often unsure of their own decisions. When users are unsure of their decision, they are very apt to go along with the community consensus, which is made visible through a social navigation system's community data.

Of particular note is that users often go along with the community consensus even when they have information that suggests a decision different than the consensus. If enough users engage in decision-making this way, the result is herding within a social navigation system, and this herding is sustained and even amplified by the system's presentation of community data. Recall, from Chapter 4, that this type of herding is an informational cascade.

In informational cascades, users who are unsure of their own expertise look to community data for guidance. Naturally, uncertain users often choose to follow the community consensus, and their decision is added to the system's community data. However, subsequent users viewing the community data assume the data derives from users with expertise rather than users who are uncertain. If enough users misinterpret community data this way, an informational cascades forms. Informational cascades lead to a false majority within a social navigation system, and the system's community data does not accurately reflect the community's knowledge. Cascades, of course, can persist for some time and can lead users to many suboptimal decisions.

## 5.5 Summary

By aggregating and presenting the choices made by others, social navigation systems can provide users with easily understandable guidance on security and privacy decisions, rather than requiring that they understand low-level technical details in order to make informed decisions. Lessons learned from Acumen and Bonfire suggest that, despite the promise of social navigation, there are significant challenges in applying these techniques to the domains of end-user privacy and security management. Due to features of these domains, individuals may misuse community data when making decisions, leading to incorrect individual decisions, inaccurate community data, and informational cascades.

By understanding this phenomenon in these terms, it is possible to begin formulating methods to improve the design and use of social navigation in both end-user privacy and security management and other domains. Chapter 8 discusses how an informational cascades perspective can inform novel features of social navigation systems.

## **CHAPTER 6**

### **AN EXPERIMENT TO INVESTIGATE THE SOCIAL NAVIGATION USER EXPERIENCE: DESCRIPTION**

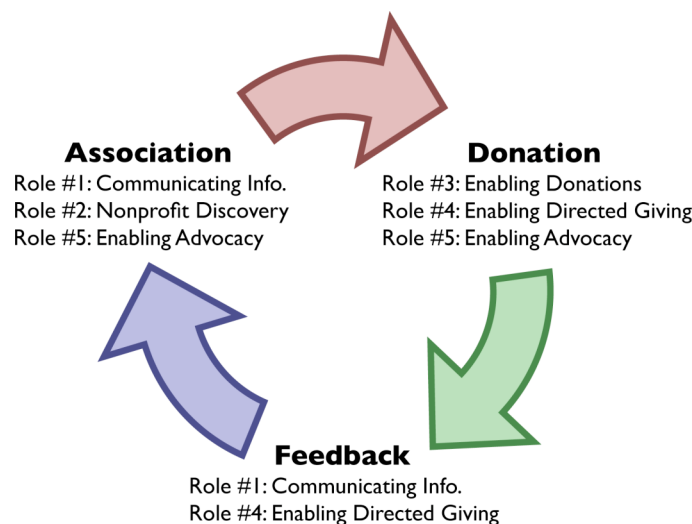
Chapter 4 developed five hypotheses about the social navigation user experience. This chapter describes the *nonprofit choice experiment*, an experiment to evaluate these hypotheses and explore the social navigation user experience more broadly. The experiment's focus is a simple social navigation system for the nonprofit fundraising domain; the purpose of the system is to help users decide whether to make a donation to a nonprofit organization. The experiment's structure is based on informational influence experiments (Baron et al., 1996; Deutsch & Gerard, 1965) and informational cascades experiments (Anderson & Holt, 1997, 2006).

This experiment is, to the best of my knowledge, the first experiment to evaluate whether community data from a social navigation system exerts informational influence, whether cascade behavior occurs in social navigation systems, and how users employ a combination of objective knowledge and community data to make decisions. This organization of this chapter is as follows. I first describe the motivation for this experiment and the overall structure of the experiment; next, I discuss the decision scenarios, which comprise the heart of the experiment, and finally participant recruiting.

#### **6.1 Experiment Motivation: Social Navigation for Online Nonprofit Giving Decisions**

Previous research (Goecks, Volda, Volda, & Mynatt, 2008) indicates that three phases comprise the “online fundraising cycle”: association, donation, and feedback (Figure 6.1). Associations between donors and nonprofit organizations lead donors to make donations to organizations, and successful feedback about past donations can lead to stronger association and additional donations, thereby reinforcing and perpetuating the cycle. The phases in this cycle correspond with traditional nonprofit fundraising models [e.g. (Klein, 2006)]. This model also connects six important roles of technology within the domain to the phase(s) in which they are prominent. The six roles that computational technology plays in the nonprofit giving domain: (1) communicating information about nonprofits; (2) helping potential donors discover nonprofits; (3) enabling donations; (4) enabling directed giving; (5) enabling individual and community advocacy; and (6) helping nonprofit organizations learn about technology use.

Particularly important to the association phase is the first role of technology, communicating information. Two of the most important factors that donors cite as reasons for donations are having trust in the nonprofit and having a relationship with that nonprofit (Cone Inc., 2006). Information sharing and



**Figure 6.1** The technology-assisted donation lifecycle.



communication are often critical for facilitating trust and fostering a relationship between donors and a nonprofit organization. One of the most basic roles of technology in nonprofit fundraising, then, is enabling the publication and communication of nonprofit organization's activities, goals and impact to potential donors. A nonprofit's online presence includes its website, its online advocates, the blogs that it sponsors, its presence in virtual environments like Second Life, and its information on third-party sites.

Third party organizations are increasingly aggregating and analyzing public information to provide donors with insight into particular facets of nonprofit organizations. Two prominent third parties, Guidestar<sup>16</sup> and Charity Navigator<sup>17</sup>, aggregate financial data from IRS 990 forms; all registered U.S. nonprofits must file an IRS 990 tax form in order to receive nonprofit tax status, and these forms are publicly available. GuideStar indexes 990 data so that it can be searched and compared; Guidestar provides numerous types of information, including past and present goals, the number of employees and volunteers, financial data (e.g., endowment, revenue sources and expenses), locations served, and board members.

Charity Navigator (Figure 6.2) is a “watchdog” organization that uses 990 data to rate nonprofits on their financial efficiency using a 5-star system. Financial efficiency ratings provide information about how efficiently a nonprofit organization employs its donations; a high efficiency rating indicates that a nonprofit directs most of its donation towards programs and services rather than administration, fundraising, or other expenses. There are other watchdog

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<sup>16</sup> <http://www.guidestar.org/>

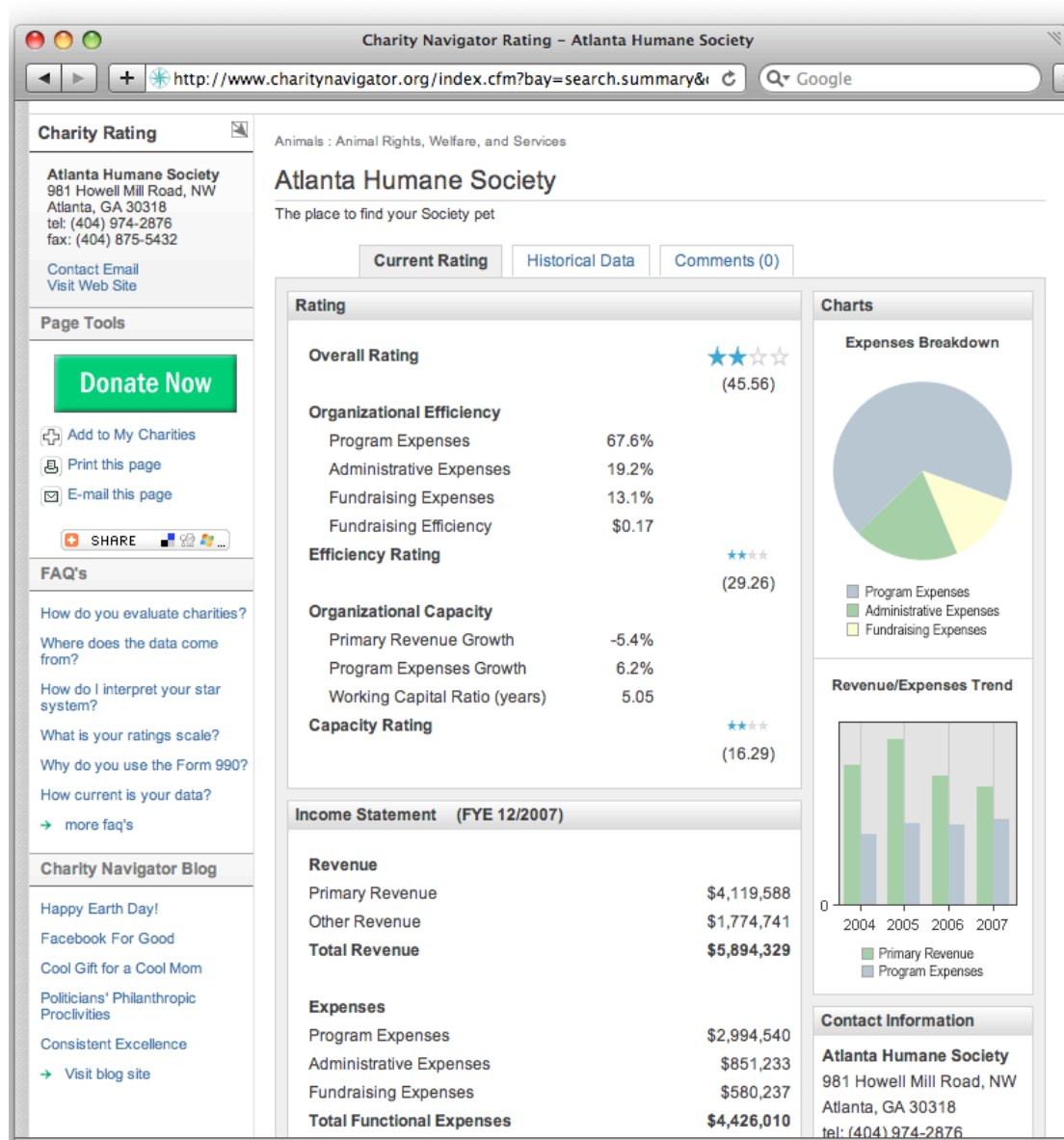
<sup>17</sup> <http://www.charitynavigator.org/>

organizations as well, and the majority measure some form of nonprofits' financial efficiency. Donors generally perceive a nonprofit with a high efficiency rating to be effective and hence worthy of a donation because most of their donation goes directly toward furthering the charity's primary mission. Other prominent United States nonprofit watchdog organizations include The American Institute of Philanthropy<sup>18</sup> and the Better Business Bureau<sup>19</sup>. While there are drawbacks to evaluating a charity via financial efficiency ratings (National Council of Nonprofits, 2005), efficiency ratings are a simple and popular information source for donors.

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<sup>18</sup> <http://www.charitywatch.org/>

<sup>19</sup> <http://www.bbb.org/us/charity/>



**Figure 6.2** Charity Navigator webpage for a nonprofit organization.

The watchdog organizations are an example of a general and powerful change that technology has brought to the nonprofit fundraising domain. Online intermediaries are providing novel types of information about nonprofits to potential donors, and donors are using this information to make more informed decisions regarding which organizations to direct their donations towards.

Social navigation systems, then, are a natural class of intermediary for the nonprofit fundraising domain as they provide an additional source of information

in the form of other people's action and opinions. Previous research shows others' actions influence both the participation (donation) rate and participation amount. Studies show that participation rate increase when a potential donor can see others donating (Bryan & Test, 1967), a list of people who have donated (Reingen, 1978), and statistics that demonstrate high response rates to solicitations (Frey & Meier, 2004). Donation amounts are also influenced by others' previous decisions. When individuals are informed of what others have donated, they adjust their donation amount toward others' donation amount, though the adjust downward more readily than upward (Croson & Shang, 2008).

Two websites, Great Nonprofits<sup>20</sup> and Change.org<sup>21</sup>, highlight the potential of social navigation in the nonprofit fundraising domain. Great Nonprofits enables many different types of stakeholders—including donors, volunteers, employees, corporate partners, and beneficiaries—to discuss, rate, and review nonprofits. Because different stakeholders can comment on a nonprofit organization, the organization's community data—discussions, ratings, and reviews—can provide a more complete picture of a organization than can other sites where only a single type of stakeholders (e.g. donor) provides feedback. Each individual that provides feedback about an organization states their role when interacting with the organization, a rating on a 5-star scale, a short comment on their experience. In addition, individuals are guided by incomplete sentences to provide particular types of especially useful feedback. Individuals can choose to complete sentences such as "I've seen the results of this organization in...", "My experience would have been better if...", and "The kinds of staff and volunteers that I met were...."

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<sup>20</sup> <http://www.greatnonprofits.org/>

<sup>21</sup> <http://www.change.org/>

Change.org is a website that enables users to organize, communicate, and take action based on shared goals called “Changes.” Example Changes include ‘Stop Global Warming’ and ‘Improve Public Schools.’ Any user can create a Change and join a Change’s group. Associated with each Change group are numerous types of user-generated content such as the names of preferred politicians, links to related resources, and group impact measures such as the number of group members, actions taken on behalf of the Change, and total donations contributed by the group. Change.org also enables group members to cultivate a list of nonprofit organizations for the Change. Group members can add to the list, comment on organizations in the list, vote (positive or negative) on organizations, view the amount of money donated to organizations by group members, and donate to an organization.

In summary, then, technology is increasing the number of information sources that donors can use to make informed decisions about online nonprofit decisions. Two of the most prominent information sources are watchdog financial efficiency ratings and community data from a social navigation system. However, the impact of these information sources on donors’ decisions—together or separately—has not been studied. This experiment explores the impact of these information sources on decision making and, at the same time, affords evaluation of my hypotheses about the social navigation user experience.

## **6.2 Method: Procedure**

Three sections comprise the nonprofit choice experiment: a demographics survey, a scenarios section, and a nonprofit giving survey. An initial survey collects basic demographic data about participants. The second section asks participants to place themselves in the role of potential donors and make a series of decisions regarding whether they would make a donation to different nonprofit

organizations. For each nonprofit that a participant is asked to make a decision for, she is provided with two types of data, financial efficiency ratings and community data from a social navigation system. Finally, the nonprofit giving section collects data about participants' nonprofit giving behaviors and priorities.

Table 6.1 lists the demographic questions that participants answered. In brief, these questions include age, gender, race, marital status, zip code (for participants in the United States), postal code (for participants in Canada), house of worship attendance, educational attainment, and occupation. All of these demographic variables have been shown to impact nonprofit donations both online (Convio, Sea Changes Strategies, & and Edge Research, 2008; Flannery, Harris, & Rhine, 2008; Network for Good, 2007) and offline (O'Neill, 2002).

**Table 6.1** Demographic questions and potential answers.

<b>Demographic</b>	<b>Categories</b>	
Age	<ul style="list-style-type: none"> <li>• 18-24</li> <li>• 25-30</li> <li>• 31-35</li> <li>• 36-40</li> <li>• 41-45</li> </ul>	<ul style="list-style-type: none"> <li>• 46-50</li> <li>• 51-55</li> <li>• 55-60</li> <li>• 61-65</li> <li>• 65 and older</li> </ul>
Gender	<ul style="list-style-type: none"> <li>• Male</li> </ul>	<ul style="list-style-type: none"> <li>• Female</li> </ul>
Educational Attainment	<ul style="list-style-type: none"> <li>• Some High School</li> <li>• High School Degree</li> <li>• Some College</li> <li>• College (Bachelor's) Degree</li> </ul>	<ul style="list-style-type: none"> <li>• Some Graduate School</li> <li>• Graduate/Professional Degree</li> <li>• Prefer not to answer</li> </ul>
Race	<ul style="list-style-type: none"> <li>• White</li> <li>• Black</li> <li>• Asian</li> </ul>	<ul style="list-style-type: none"> <li>• Hispanic</li> <li>• Other</li> <li>• Prefer not to answer</li> </ul>
Occupation	<ul style="list-style-type: none"> <li>• Professional/Technical</li> <li>• Administrative/Managerial</li> <li>• Legal/Lawyer</li> <li>• Sales/Service</li> <li>• Teacher/Educator</li> <li>• Law Enforcement</li> <li>• Clerical/White Collar</li> <li>• Craftsman/Blue Collar</li> </ul>	<ul style="list-style-type: none"> <li>• Student</li> <li>• Homemaker</li> <li>• Engineer/Scientist</li> <li>• Academic/Researcher</li> <li>• Unemployed/Looking for Work</li> <li>• Retired</li> <li>• Prefer not to answer</li> </ul>
Annual Household Income	<ul style="list-style-type: none"> <li>• Less than \$10,000</li> <li>• \$10,000 - \$24,999</li> <li>• \$25,000 - \$39,999</li> <li>• \$40,000 - \$54,999</li> <li>• \$55,000 - \$69,999</li> <li>• \$70,000 - \$84,999</li> </ul>	<ul style="list-style-type: none"> <li>• \$85,000 - \$99,999</li> <li>• \$100,000 - \$149,999</li> <li>• \$150,000 - \$199,999</li> <li>• \$200,000 - \$299,999</li> <li>• More than \$300,000</li> <li>• Prefer not to answer</li> </ul>
Church Attendance	<ul style="list-style-type: none"> <li>• Once a week or more</li> <li>• Once or twice a month</li> <li>• Once every couple months</li> </ul>	<ul style="list-style-type: none"> <li>• Once or twice a year</li> <li>• Never</li> </ul>
Marital Status	<ul style="list-style-type: none"> <li>• Single</li> <li>• In a Committed Relationship</li> <li>• Married</li> </ul>	<ul style="list-style-type: none"> <li>• Divorced/Widowed</li> <li>• Other</li> </ul>
Zip Code (U.S) / Postal Code (CA)	<ul style="list-style-type: none"> <li>• Open</li> </ul>	

Table 6.2 lists the nonprofit giving questions that participants answered. One set of questions asked participants to indicate which nonprofit organizations and which types of organizations they donated to, how often they donated, how much they donated, and their priorities for future donations. Table 6.3 lists the types of nonprofit organizations and the examples of each type that were provided to participants. Another set of questions were free form and asked participants to describe what factors influenced their donation decisions, how they got information about these factors, and why they made online donations rather than offline donations. Many of these questions are based on other surveys on online nonprofit giving (Convio et al., 2008; Flannery et al., 2008; Network for Good, 2007).



**Table 6.2** Nonprofit giving questions and potential answers.

<b>Question</b>	<b>Answers</b>
During the last two years, which of the following types of charitable/nonprofit organizations have you made donations towards?	<ul style="list-style-type: none"> <li>• See Table X.3</li> </ul>
Please list all the charities/nonprofit organizations that you have made donations towards during the last two years.	
During the last two years, about how often have you made contributions to charities/nonprofit organizations?	<ul style="list-style-type: none"> <li>• Once a week or more</li> <li>• Once or twice a month</li> <li>• Once every couple months</li> <li>• Once or twice a year</li> <li>• Less than once per year</li> </ul>
During the last two years, what size contribution have you made most often to charities / nonprofit organizations?	<ul style="list-style-type: none"> <li>• Less than \$20</li> <li>• \$20-\$49</li> <li>• \$50-\$74</li> <li>• \$75-\$99</li> <li>• \$100-\$199</li> <li>• More than \$200</li> </ul>
Please rank these areas in terms of your expected future charitable donations during the next two years	<ul style="list-style-type: none"> <li>• See Table X.3</li> </ul>
Are there situations or circumstances where you choose to make charitable contributions online rather than using other methods? For which circumstances are you most likely to make contributions online?	<ul style="list-style-type: none"> <li>• Free text</li> </ul>
What are the most important factors to you when considering which charities/nonprofits to make contributions towards? Where do you get information on these factors?	<ul style="list-style-type: none"> <li>• Free text</li> </ul>

**Table 6.3** Categories for nonprofit organizations and examples used in experiment's nonprofit giving questions.

<b>Nonprofit Category</b>	<b>Examples</b>
Arts, Culture, Humanities	Local museum, symphony
Environment & Animals	Park conservancy, environment preservation
International Affairs	Third world medical care, education, or economic support
Foundations	Gates Foundation, Rockefeller Foundation
Religion	Your local church
Education	Local elementary school or university, after-school programs
Health	Cancer research, local hospital
Human Services	A homeless shelter, mentoring
Public-society Benefit	Public zoo, public radio

### 6.3 Scenarios Section / Donation Scenarios

The core of the experiment is the scenarios section. In this section, participants are asked to place themselves in the role of a potential donor and decide whether they would make donations to different nonprofits. For each nonprofit that a participant is asked to make a decision for, she is provided with two types of data, financial efficiency ratings and community data from a social navigation system.

Figure 6.3 shows a screenshot of a trial in the experiment. A participant is asked whether he would make a donation to an anonymous nonprofit organization, and he must select either ‘yes’ or ‘no.’ The participant can see financial efficiency ratings from up to three watchdog organizations and community data summarizing the decisions made by previous participants. There

**Scenario 9**

*Choose one of the following answers*

**Would you make a donation to this Nonprofit Organization?**

*You can mouse over the data in the table to get more information.*

	<b>Watchdog Financial Efficiency Ratings</b> A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated. key: ✓ = high, ✗ = low, [icon] = unavailable			<b>Choices by Other People (15)</b> A summary of the choices that previous participants in this experiment have made for this nonprofit. These participants may have seen ratings from watchdogs ABE or SUR. 15 participants have already chosen.	
	ABE	NEL	SUR	Yes	No
<b>A Nonprofit Organization</b>	[icon]	✗	[icon]	[15 icons]	[3 icons]

**Would you make a donation to this organization?**

Yes ☐ No ☐

**Figure 6.3** Scenario or decision trial in the nonprofit experiment: a participant is asked to decide whether he would make a donation to this nonprofit. Two data sources are available: (a) watchdog financial efficiency ratings and (b) community data from a social navigation system. One watchdog rating is visible (NEL), and two watchdog ratings are hidden (ABE, SUR). The community data disagrees with the watchdog rating, and hence the participant must choose to follow either the watchdog rating or the community data.

are many scenarios in which one or two watchdog ratings are hidden, but community data is always visible.

In the experiment, financial efficiency ratings have two possible values: high (green checkmark) or low (red X). Most watchdog organizations rate nonprofits on an ordinal scale such as Charity Navigator's zero to five star scale and The American Institute of Philanthropy's A-F grading scale. The experiment employs a simpler scale with only two values for three reasons: (1) participants can more easily understand the ratings data and thus the experiment takes less time; (2) analyzing participants' decisions is simpler; and (3) similar experiments in other bodies of research, which I discuss below, use a 2-value scale as well.

The other data source that a participant has when making decisions is community data from a social navigation system. The community data is ostensibly a summary of the decisions that previous participants have made for a particular nonprofit; in fact, the community data is carefully constructed to evaluate critical decisions that users may encounter when using both data types to decide whether they would make a donation to a nonprofit organization. The depiction of the community data is quite simple: small icons that look like people denote the number of other participants that have (ostensibly) made a particular choice for a nonprofit. This depiction is an absolute representation of the community data rather than a relative or saturation representation.

A critical facet of the experiment is convincing participants that the community data derives from other participants who potentially have seen different watchdog ratings. It is very important that participants hold this belief because community data can exert informational influence only if a participant believes that other people may know information that she does not.

In order to instill this belief in participants, participants begin the experiment by walking through a set of three example scenarios that make this belief explicit. Figures 6.4, 6.5, and 6.6 show the three example scenarios. The first example introduces participants to watchdog ratings and what they mean. The second example shows participants that some watchdog ratings may be temporarily unavailable and provides standard reasons for why ratings may be unavailable (e.g. connectivity issues, website down, data updates). The third example instills the belief that other participants may have seen ratings that the current participant cannot see by explicitly stating it. In addition, the text in the organizational data table that describes watchdog ratings and community data reinforces this belief. After viewing the three examples, participants answer 14 randomly-selected scenarios.

**Example 1: Financial Efficiency Ratings**

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**Would you make a donation to this Nonprofit Organization?**

You can mouse over the data in the table to get more information.

	<p><b>Watchdog Financial Efficiency Ratings</b></p> <p>A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated.</p> <p>key: ✓ = high, ✗ = low, ⚡ = unavailable</p>		
	ABE	NEL	SUR
<b>Nonprofit Organization #1</b>	✓	✗	✓

Here are some things to notice about financial efficiency ratings:

- There are **3 watchdog organizations** that rate nonprofits on their financial efficiency; they have been renamed as Watchdog ABE, Watchdog NEL, and Watchdog SUR.
- Each watchdog rates a nonprofit as having either "**high efficiency**" or "**low efficiency**."

**Would you make a donation to this organization?**

Yes ☐      No ☐

**Figure 6.4** Example 1 in the scenarios section introduces participants to watchdog financial efficiency ratings.

### Example 2: Missing Watchdog Ratings

**Would you make a donation to this Nonprofit Organization?**

You can mouse over the data in the table to get more information.

	<p> <b>Watchdog Financial Efficiency Ratings</b>          A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated.          key:  = high,  = low,  = unavailable</p>		
	ABE	NEL	SUR
<b>Nonprofit Organization #1</b>			

Here are some things to notice:

- Watchdog NEL's rating is currently unavailable.
- Sometimes watchdog ratings are unavailable for a brief period of time; a watchdog's rating may be unavailable because
  - the watchdog's website is broken;
  - the rating is outdated;
  - the rating is being updated.

**Would you make a donation to this organization?**

Yes ☐      No ☐

**Figure 6.5** Example 2 in the scenarios section introduces participants to temporarily missing financial efficiency ratings and reasons they might be missing.

### Example 3: Choices by Other People

**Would you make a donation to this Nonprofit Organization?**

You can mouse over the data in the table to get more information.

	<p> <b>Watchdog Financial Efficiency Ratings</b>          A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated.          key:  = high,  = low,  = unavailable</p>			<p> <b>Choices by Other People (5)</b>          A summary of the choices that previous participants in this experiment have made for this nonprofit. These participants may have seen ratings from watchdogs ABE or SUR.           5 participants have already chosen.</p>	
	ABE	NEL	SUR	Yes	No
<b>A Nonprofit Organization</b>					

Here are some things to notice:

- You can now see the **choices that previous participants in this experiment have made.**
- **Other participants may have seen watchdog ratings that are currently unavailable to you.**

**Would you make a donation to this organization?**

Yes ☐      No ☐

**Figure 6.6** Example 3 in the scenarios section introduces participants to community data and instills the belief that other people may have seen ratings that they cannot see.

**Table 6.4** Feedback questions on decision-making scenarios.

Question	Answer
In the scenarios, how did you make decisions about whether you'd donate to a nonprofit organization?	<ul style="list-style-type: none"> <li>• I mostly used the watchdog ratings.</li> <li>• I mostly used the choices made by other participants.</li> <li>• I tried to combine the watchdog ratings and choices made by other participants.</li> <li>• There wasn't enough information to make a reasonable decision.</li> <li>• I used something else. (Please explain in the comment box to the right.)</li> </ul>
Please comment on any aspect of the scenarios that you feel strongly about. Were you asked to make a reasonable decision? Was the information about each nonprofit organization clear? Did this information help you make a decision or not	<ul style="list-style-type: none"> <li>• Free Text</li> </ul>

Finally, Table 6.4 details two final questions that participants encounter after they complete the 14 scenarios. These questions ask participants to indicate how they made decisions and comment on any aspects of the scenarios that they found unreasonable or frustrating. These questions serve two purposes; they allow participants to express their feelings about the scenarios' decisions, and they collect useful data about participants' decision-making processes.

### 6.3.1 Experimental Design

There are 36 potential scenarios that participants may encounter when making decisions about nonprofits. These decisions are based on a near-fully crossed factorial design with the following independent variables:

- *community data size* (5, 15, or 35 people);
- *community data unanimity* (60% or 80%);
- *number of visible watchdog ratings* (1, 2 or 3 ratings);

- *values of visible watchdog ratings* (2 ratings one direction vs. 1 rating the opposite direction, 2 vs. 0, 1 vs. 1, or 1 vs. 0);
- *agreement or disagreement between ratings and community data* (yes, no).

For example, Figure 6.3 shows a scenario where one rating is visible and is assigned a negative rating, the community data's size is 15 and unanimity is 80%, and there is disagreement between the ratings and the community data. Participants were shown a random selection of scenarios.

The two independent variables for the community data fully specify the data for each choice. The *size* is the total size of the community, and the *unanimity* determines the size of the majority and minority. Hence, if *size* is 25 and *unanimity* is 60%, then the majority is 15 and the minority is 10.

The *number* and *values of visible watchdog ratings* are coupled to yield a set of watchdog ratings. When three ratings are visible, the ratio is always two ratings in one direction and one rating in the opposite direction. This ratio is used because a three-zero ratio—all ratings the same—likely obviates any community data and makes the decision quite straightforward. When two ratings are visible, the ratio is either two-zero or one-one; when one rating is visible, the ratio is clearly one-zero. Once the *number* and *values* of ratings are chosen, they are randomly assigned to each watchdog organization. Thus, each watchdog is equally likely to provide a positive or negative rating, and the ratio of watchdog ratings is equally likely to be positive or negative.

The key variable in the construction of scenarios is the *agreement* between the community data and the watchdog ratings. When the community data and the ratings agree, they suggest the same decision; when they disagree, they suggest a different decision. Figure 6.7 shows examples of both agreement and disagreement between the ratings and the community data. When there is

	<b>\$ Watchdog Financial Efficiency Ratings</b> A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated. key: ✓ = high, ✗ = low, ⚡ = unavailable			<b>👥 Choices by Other People (35)</b> A summary of the choices that previous participants in this experiment have made for this nonprofit. 35 participants have already chosen.	
	ABE	NEL	SUR	Yes	No
<b>A Nonprofit Organization</b>	✓	✓	✗		

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	<b>\$ Watchdog Financial Efficiency Ratings</b> A high rating means most of your donation would go toward programs and services—helping people—rather than office expenses or fundraising. Ratings may be temporarily unavailable due to technical issues or because the rating is being updated. key: ✓ = high, ✗ = low, ⚡ = unavailable			<b>👥 Choices by Other People (15)</b> A summary of the choices that previous participants in this experiment have made for this nonprofit. 15 participants have already chosen.	
	ABE	NEL	SUR	Yes	No
<b>A Nonprofit Organization</b>	✓	✗	✗		

**Figure 6.7** Examples of agreement between watchdog financial ratings and community data (top) and disagreement (bottom).

agreement between the ratings and the community data, I term these scenarios as “expected” scenarios because it is expected that participants will make a decision that is suggested by both data sources. In contrast, I term the scenarios when the ratings and the community data disagree as “cascade” scenarios because these are the instances when informational cascade behavior can arise.

It is useful to combine the variables *number of visible watchdog ratings*, *values of visible ratings*, and *agreement* between ratings and community data into a single variable that I call *data configuration*. Table 6.5 lists the six possible values for *data configuration*.

Using the *data configuration* variable yields two advantages. The variable simplifies conceptualization of scenarios and participant decision data; scenarios are the result of a near fully-factored design with three variables: *data configuration*, *community data size*, and *community data unanimity*. Using the *data configuration* variable also provides ready comparisons between scenarios. For example, conditions 1 and 2 of *data configuration* afford comparison of the



**Table 6.5** Values for the independent variable *data configuration*. Variable fully qualifies the number of visible ratings, ratings' values, and whether the ratings agree or disagree with the community data.

Data Configuration		Num. Visible Ratings	Ratings' Values	Agreement with Community Data
	1	3	2 vs. 1	agreement
	2	3	2 vs. 1	disagreement
	3	2	1 vs. 1	----
	4	2	2 vs. 0	disagreement
	5	1	1 vs. 0	disagreement
	6	1	1 vs. 0	agreement

scenarios in which the community data agrees and disagrees with the watchdog ratings. Another example: the cascade conditions—conditions 2, 4, and 5—afford analysis of how participants make decisions given different numbers of visible ratings and community data that disagrees with the ratings.

### 6.3.2 Similarities and Differences between this Experiment and Other Experimental Designs

Recall that the hypotheses that drive this experiment derive from applying social influence, advice-taking, and informational cascades research to the use of community data from social navigation system. Hence, it is logical that the design of this experiment draws significantly from experiments in these bodies of research. In particular, this experiment is based largely on informational cascade experiments (Anderson & Holt, 2006) because that is the research body that I was most knowledgeable about when designing this experiment. However, there are also similarities between this experiment and social influence experiments (Bond & Smith, 1996) and advice-taking experiments (Bonaccio & Dalal, 2006). It is useful to draw similarities and differences between this experiment and experiments in these domains in order to better understand what can and cannot

be learned from this experiment and to afford comparisons between the findings from this experiment and other experiments.

A primary difference between this experiment and related experiments is its focus on computer-mediated or online social influence; other experiments have studied social influence in the physical world. However, other experiments have studies situations in which individuals employ a proxy that describes or summarizes behavior rather than directly observing behavior. Example proxies include being told what others have done and observing a stock market ticker, which is an indication of how people are valuing financial assets.

A user interface that displays community data from a social navigation system is yet another proxy for summarizing others' behaviors. To the best of my knowledge, there has not been research that compares the efficacy of different proxies. Given that many different kinds of proxies have been shown to impact human behavior, though, it is reasonable to conjecture that people are adept at interpreting and employing different proxies to reason about the human behavior that they depict. Thus, there is reason to expect that individuals can readily utilize the proxy that is a social navigation system and its interface.

This experiment draws significantly from informational cascade experiments. The standard format for informational cascades experiments is as follows. First, the experiment administrator randomly chooses a "world state" to be one of two urns; one urn has 2 black balls and 1 white ball, and the other urn has 2 white balls and one black ball. Using Bayes' theorem, each ball is likely to be 66% accurate. Participants are then ordered and a series of decisions are prompted using a standard protocol. The first participant, in private, selects a ball from the chosen urn and, based on his selection, makes a decision about which urn she believes was chosen. Her decision is made public—but not the color of the ball

she selected—to the other participants. Subsequent participants also select in private but can use their selection *and other participants' previous decisions* to make their decisions. Cascade behavior arises when a participant ignores her private information—the color of the ball he selected—and makes a decision that agrees with the community consensus. After all participants have made their decisions, participants that made the correct decision earn a reward, regardless of how they made their decision.

The key similarity between this experiment and informational cascade experiments is that the two information sources in this experiment, the watchdog financial efficiency ratings and community data, parallel the information sources in informational cascade experiments. The three watchdog ratings are equivalent to the three balls used in cascade experiments. Pilot testing suggested that participants were confused about seeing a random watchdog rating on a user interface because they expect computer interfaces to be able to provide all available information; hence, I developed the notion of “missing or unavailable” ratings in order to control what ratings participants saw. Nonetheless, the effect is the same: a participant sees a limited and imprecise signal but sees all community data, and she must make a decision based on this information.

There are two important differences between this experiment and informational cascade experiments (Anderson & Holt, 2006). First, unlike cascade experiments, there is no correct answer that can be used to evaluate participants' decisions in this experiment. In cascade experiments, participants employ an externally imposed and uniform decision criterion. Similarly, I could have asked participants to make a donation to a nonprofit only if they believed that it had a majority of positive ratings. I chose not to make the decision criterion uniform because it is difficult to convey a uniform decision criterion while ensuring that participants engage with the decisions authentically.

Because there is not a uniform decision criterion in this experiment, I cannot evaluate the efficacy of the social navigation system. However, I can identify social influence and cascade behavior among participants and thus can evaluate my hypotheses about the social navigation user experience. In addition, because participants use their own decision criteria, this experiment can provide insight into these criteria.

The other important difference between this experiment and informational cascade experiments is the decision type or structure. In cascade experiments, both answers are similar because they carry equal consequences. In this experiment, however, a decision to make a donation to a nonprofit organization theoretically carries more consequences than a decision to abstain from making a donation. In other words, in this experiment, participants can provide a theoretically cost-free answer of “no.” The presence of answers that have different costs and consequences likely changes how individuals make decisions in this experiment as compared to decisions in informational cascade experiments.

There is a key similarity that this experiment and social influence experiments (Bond & Smith, 1996) share: both often manipulate the information available to participants and hence the difficulty of the decision. The less information participants have, the more difficult it is to make a decision well. It is interesting to note that informational cascade experiments do not manipulate the amount of information that participants have when making decisions; instead, they hold constant the amount of information that participants have, and this amount is quite small.

The principal difference between this experiment and social influence experiments (Bond & Smith, 1996) is the type of decision that participants make. In social influence experiments, many decisions are simple, perceptual decisions

such as line-length or eye-witness matching. The decision in this experiment, to make or withhold a charitable donation, is more complex and draws on not only perception but also personal preferences. A smaller difference concerns the manipulation of incentives for correct decisions: this experiment does not manipulate the incentives for participants to make correct decisions, but many social influence experiments do and have shown that this can impact participants' decisions. I choose to hold the incentives constant in my experiment in order to mirror an authentic donation decision in which choosing to withhold a donation is cost-free and choosing to make a donation incurs costs.

While the notion of advice in advice-taking experiments (Bonaccio & Dalal, 2006) is analogous to providing community data in my experiment, there are significant differences between advice-taking experiments and this experiment. Advice-taking experiments typically employ a continuous decision scale rather than a set of discrete choices; in contrast, participants in my experiment choose from a very small number of discrete choices. Hence, in my experiment, it will be difficult to assess how much community data impacts particular decisions. Advice-taking experiments also often assess how the qualities of advice providers—such as expertise—while my experiment does not explore this variable.

#### **6.4 Participant Recruiting**

I conducted this experiment online, following best practices in conducting Internet experiments (Reips, 2002). I recruited participants by personal request and by advertising on email lists, online forums, search results, and social networking websites.

I designed a unique incentive plan for participation in this experiment in order to attract participants that had an interest in fostering and making online

nonprofit donations. The incentive plan is based on a *donation pool* that was to be donated to a nonprofit organization at the completion of the experiment. When a participant completed the experiment, \$2 was added to the donation pool and the participant could choose to vote for a nonprofit that he wanted to receive the donation pool. At the completion of the study, the nonprofit with the most votes received the donation pool as a charitable donation. Thus, the incentive for participants to complete the experiment was the generation of a small charitable contribution and a vote for a nonprofit that he wanted the donation pool to go towards.

The nonprofits that participants could vote on included Big Brothers Big Sisters<sup>22</sup>, Doctors Without Borders<sup>23</sup>, DonorsChoose<sup>24</sup>, and UNICEF<sup>25</sup>. I chose these nonprofits because they demonstrate impact on a national or international scale, are generally seen as secular and apolitical, and provide for basic human needs. Moreover, these nonprofits are amongst the most highly rated in terms of impact and efficiency by Charity Navigator and the American Institute of Philanthropy.

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<sup>22</sup> <http://www.bbbs.org/>

<sup>23</sup> <http://www.doctorswithoutborders.org/>

<sup>24</sup> <http://www.donorschoose.org/>

<sup>25</sup> <http://www.unicef.org/>

## CHAPTER 7

### AN EXPERIMENT TO INVESTIGATE THE SOCIAL NAVIGATION USER EXPERIENCE: ANALYSES AND FINDINGS

This chapter discusses data, analyses, and findings from the *nonprofit choice experiment* that Chapter 6 describes. The focus of this chapter is investigating the five hypotheses that motivate this experiment.

#### 7.1 Hypotheses and Divisions among Scenario Conditions

The five hypotheses for this experiment are:

**Hypothesis 1:** *Community data from a social navigation system exerts informational influence on participants.*

**Hypothesis 2:** *Individuals perform egocentric discounting on community data from a social navigation system.*

**Hypothesis 3:** *Herding behavior in social navigation systems can be characterized as informational cascade behavior.*

**Hypothesis 4:** *The size of the group that the community data represents directly correlates with the strength of the community data's social influence.*

**Hypothesis 5:** *The unanimity of the group's consensus that the community data represents directly correlates with the strength of the community data's social influence.*

These hypotheses suggest two key distinctions among the scenario conditions. Recall that there are 36 potential conditions that a participant may encounter in the decision scenarios; the variables that define the conditions are the number

and ratio of visible watchdog ratings, the size and unanimity of community data, and whether the visible ratings agree with the community data.

One very important distinction among conditions is the agreement or disagreement between the two data sources, ratings and the community data. I term the conditions when there is agreement between the data sources as *non-cascade* conditions and term the conditions where there is disagreement between the data sources as *cascade* conditions. This terminology is descriptive as cascade behavior—ignoring personal information and making a choice that instead agrees with community consensus—is possible only in cascade conditions.

The division between cascade conditions and non-cascade conditions is important because the type of decision differs between each condition set. In cascade conditions, participants see disagreement among the data sources; thus, their choice reveals that they agree with one data source more than the other. In non-cascade conditions, however, participants see agreement among data sources, and their choice in these conditions is to agree or disagree with all data.

Another key distinction among conditions is the decision that the community data suggests. For cascade conditions, the suggested decision differed from that suggested by the ratings; for non-cascade conditions, the suggested decision is suggested by both the ratings and the community data. As discussed in Chapter 6, the theoretical cost of making a donation—a *Yes* decision—is significant, but the theoretical cost of withholding a donation—a *No* decision—is free. Given this decision structure, I hypothesize that participants may employ watchdog ratings and community data differently depending on whether they suggest making or withholding a donation.

Hence, in the cascade conditions, there is a meaningful distinction based on the decision that the community data suggests: (a) conditions in which the



watchdog ratings suggest making a donation and the community data suggests withholding a donation and (b) conditions in which the watchdog ratings suggest withholding a donation and the community data suggests making a donation. In non-cascade conditions, the distinction is different because the watchdog ratings and community data suggest the same decision. The distinction in non-cascade conditions, then, arises between conditions in which the ratings and community data suggest making a donation and conditions in which the information suggests withholding a donation.

These two divisions yield seven condition sets, and I analyze decision data from each of these condition sets using the following structure:

1. all conditions;
2. all cascade conditions;
  - cascade conditions in which ratings suggest *Yes* and community data suggests *No*;
  - cascade conditions in which ratings suggest *No* and community data suggests *Yes*;
3. all non-cascade conditions;
  - non-cascade conditions in which the suggested answer is *No*;
  - non-cascade conditions in which the suggested answer is *Yes*.

These conditions sets afford evaluation of Hypotheses 1, 2, and 3.

Hypotheses 4 and 5 posit that the size and unanimity of community data will positively correlate with the community data's impact on participants' decisions. That is, all things equal, community data denoting a larger size group will have more impact than community data denoting a smaller group, and community data denoting a group with a stronger consensus will have more impact than community data denoting a group with less consensus. Surprisingly, no

evaluations of social navigation systems have investigated the impact of the community data's size and unanimity. Most studies of social influence (Bond & Smith, 1996) and informational cascades (Anderson & Holt, 2006) consider the impact of decisions made a small group—usually three to twenty people—on an individual's decision. In contrast, community data can represent the decisions made by much larger groups. To evaluate Hypotheses 4 and 5, I analyze the impact of the community data's size and unanimity on the decision data on each set and subset of cascade and non-cascade conditions.

## **7.2 Analysis of Decision Data from All Conditions: Participant**

### **Demographic Data & The Dominant Choice in Conditions**

My analysis of decision data from all conditions focuses on participants' demographic data and the dominant decision choice in the conditions. I discuss both in turn.

#### **7.2.1 Participant Demographic Data**

Table 7.1 summarizes the demographic data for the experiment's participant population. To participate in the experiment, participants must have met two criteria: (1) be at least 18 years old and (2) have made an online donation to a nonprofit organization. These criteria ensure that participants have been and, in the future, could be online donors to nonprofit organizations. 215 people completed the experiment; about 40% of participants were male and 60% were female. The great majority of participants resides in the United States, are between the ages of 18 and 40, and have a college degree. Participants varied widely in job type, household income, and church attendance.

It is useful to determine how this experiment's population is and is not representative of the broader nonprofit giving population; this information can

**Table 7.1** Summary of participants' demographic data.

<b>Feature</b>	<b>Summary/ Major Categories</b>
Number of Participants	215
Country of Residence	95% United States, 5% Canada
Gender	38% Male, 62% Female
Age	75% 18-40 years old
Education	97% have a college bachelor's degree or advanced degree
Race	84% Caucasian
Occupation	29% White Collar Job, 23% Academia
Household Income	Roughly even distribution from \$25,000/year to \$200,000/year
Church Attendance	40% never attend, 25% attend at least once/month

inform how and to what degree the results of this experiment generalize to broader populations. Because this experiment focuses on online nonprofit giving and because the great majority of this experiment's participants reside in the United State, I compare this participants' demographic data with that from other surveys of online nonprofit giving by U.S. residents.

First consider participants' gender. The Network for Good study of online nonprofit giving (Network for Good, 2007) reports that 52% of online donors are female. The 2008 DonorCentrics and Internet Giving Benchmark Survey (Flannery et al., 2008) reports a similar percentage of female donors but also reports that the percentage of online male donors is increasing, albeit slowly. Females, then, are overrepresented in this experiment while males are underrepresented.

Next consider participants' ages. The Network for Good (NfG) survey reports that the average age of online donors is 38-40, and the DonorCentrics (DC) survey reports that 75% of online donors are distributed equally between the ages of 35 and 64. Thus, the participants in the experiment are, on average, slightly younger than the average Internet donor.

Next consider participants' household income. The household income that participants in this experiment reported is the same as that reported in the DC survey; the NfG survey does not report household income. Household income for participants' in this experiment, then, is representative of online donors.

Lastly, consider participants' education, race, occupation, and church attendance. Neither the NfG survey nor the DC survey reported data for these demographics features, but another survey of middle and major online donors does provide most such data (Convio et al., 2008). Race and household income distributions reported by this survey of middle and major donors (MMD) are similar to the race and household income distributions of participants in this experiment. As compared to occupation distributions in the MMD survey, this participants in this experiment overrepresent academic workers and underrepresent white-collar workers. The MMD survey provides no data on church attendance.

In summary, the participants in this experiment are somewhat though not markedly atypical as compared to the overall online donor population. However, there are numerous similarities between participants in this experiment and middle and major online donors. Participants in this experiment, then, are more representative of middle and major online donors than of the overall online donor population.

### **7.2.2 The Dominant Choice Suggests that Participants Provided Authentic Responses**

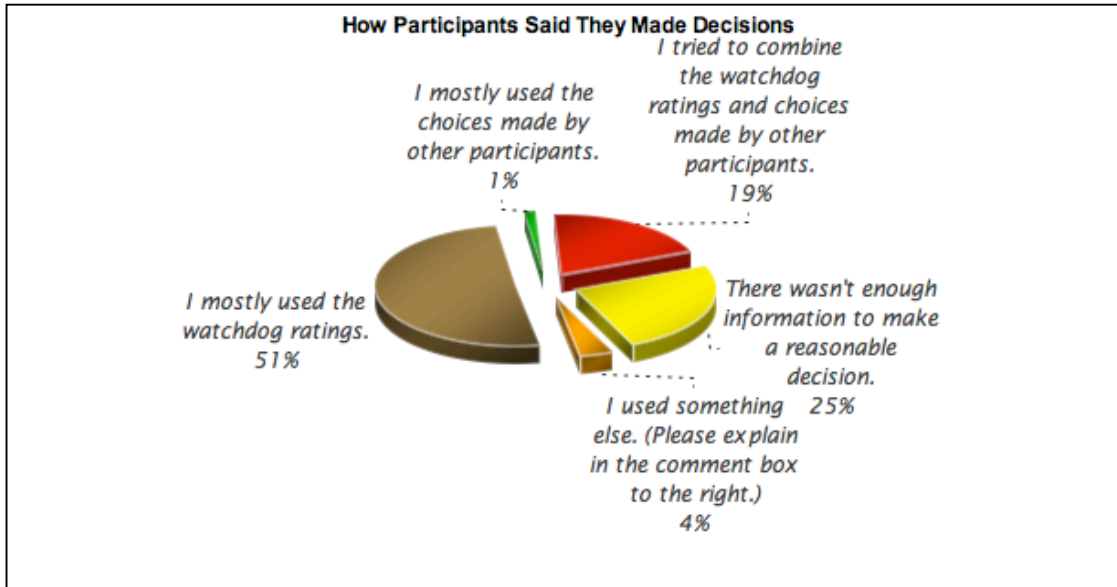
Participants answered *No* in 75% of all decisions despite the community data and ratings being equally balanced in both directions throughout all conditions. This is a striking finding due to its strength, and there are two implications of this finding. First, the division of conditions based on whether the community data

suggests a *Yes* decision or *No* decision is likely meaningful. Second, a high percentage of *No* decisions indicates that participants likely provided authentic answers to the scenario questions. Earlier it was argued that the decision structure for making a donation is such that there is a theoretical cost of answering *Yes*, but the cost of answering *No* is free. The high percentage *No* decisions supports this argument.

Moreover, additional data from the experiment indicates that participants generally said that they would not make donations to nonprofit organizations in the scenarios because they were skeptical of making a donation to an unknown nonprofit with limited information and, when they were unsure of a decision, they chose the cost-free answer of *No*. Participants' expressed frustration because they had limited information about a nonprofit (e.g. a nonprofit's mission and size were unavailable). Participants initially expressed this frustration by sending unsolicited emails to the contact email address for the experiment. Based on these emails, I added the two questions after the scenarios that asked participants to answer how they made their decisions and to express any frustrations or challenges they had when answering these questions. 77 participants answered these questions.

Figure 7.1 provides a breakdown of users answers to the question "*In the scenarios, how did you make decisions about whether you'd donate to a nonprofit organization?*" Nearly 25% of participants said they did not have enough information to make decisions, indicating that these participants were often frustrated by information they would have preferred to have when making these decisions. Here are some quotes from participants about the decisions they were asked to make in the scenarios:

**P1:** *"The information was clear, but I chose "no" for most of the scenarios, because in a real world scenario, I would not donate to an organization I had insufficient*



**Figure 7.1** Summary of participants' answers to the question "In the scenarios, how did you make decisions about whether you'd donate to a nonprofit organization?"

*information about. I keep a folder in my file cabinet related to charitable contributions, so if I had insufficient information, I would make a note of it in the folder, and revisit it when I was able to get more information. If later I still could not find a level of information I was happy with, I would probably stop considering that charity as a possible beneficiary of my contributions."*

**P2:** *"My decisions relating to a charity would not only involve responsible use of their money, but also a clear purpose that I agree with and helps others."*

**P3:** *"I make decisions about service, impact, people served. Making a decision just about ratings isn't how I would actually make a gift. The mission and services would drive the donation and then I would decide between nonprofits with help from other criteria."*

**P4:** *"I do weigh the efficiency of the organization when deciding to make a donation, but there are also many other factors--like to mission of the organization, or the values of the person for whom I am making a donation in honor/memory of."*

**P5:** *"For this experiment, I primarily used the watchdog ratings, since that was the only information available to make a choice. I tend to weigh a lot more factors when actually making this decision. Whether or not I have money or if I believe strongly*

*in the cause seem to matter more when I am deciding to give. But I will not give at all if I don't trust the charity or believe it is legitimate.”*

Based on the quantitative data and participants’ quotes, it is clear that donors use the watchdog ratings to make donations decisions. However, ratings are a less important information source than other factors, such as a nonprofit’s purpose and values. In retrospect, the experiment should have framed the question more concisely in order to mitigate these more important factors in order to encourage participants to focus on the information available rather than the information that was not. Nonetheless, because ratings are a factor in decision making and because other facets of a nonprofit were hidden, the decisions participants made are valid.

Most importantly, the sum of this data—a significant bias toward *No* answers and frustration about a lack of information—provides evidence that participants engaged with the decisions and made authentic choices. This evidence increases the credibility of the experiment’s data and results.

### **7.3 Analysis of Decision Data from Cascade Conditions**

Recall that there are three different conditions in the cascade conditions: (a) one rating is visible; (b) two ratings are visible and are the same; and (c) three ratings are visible, and two ratings are the same and the third is different. Of course, in all cascade conditions, the community data suggests a different decision than do the ratings. For instance, two ratings may be low, and thus the ratings suggest withholding a donation from the nonprofit, but the community data shows that the majority of other participants answered that they would make a donation.

My analysis of decision data from cascade conditions begins by investigating Hypothesis 1—does community data exert informational influence?—and

Hypothesis 3—can herding in social navigation systems be characterized as informational cascades? Next, I evaluate the differences between conditions in which the community data suggests a *Yes* decision and the watchdog ratings suggest *No* and conditions in which the community data suggests *No* and watchdog ratings suggest *Yes*. Finally, I consider how the size and unanimity of community data impact participants' decisions.

Throughout this discussion, a key measurement is the social influence of the community data. This is measured by calculating how often participants made a choice that agreed with the community consensus—represented by the community data—as compared to how often they made a choice that agreed with the ratings.

### **7.3.1 Finding: Community Data exerts Information Influence**

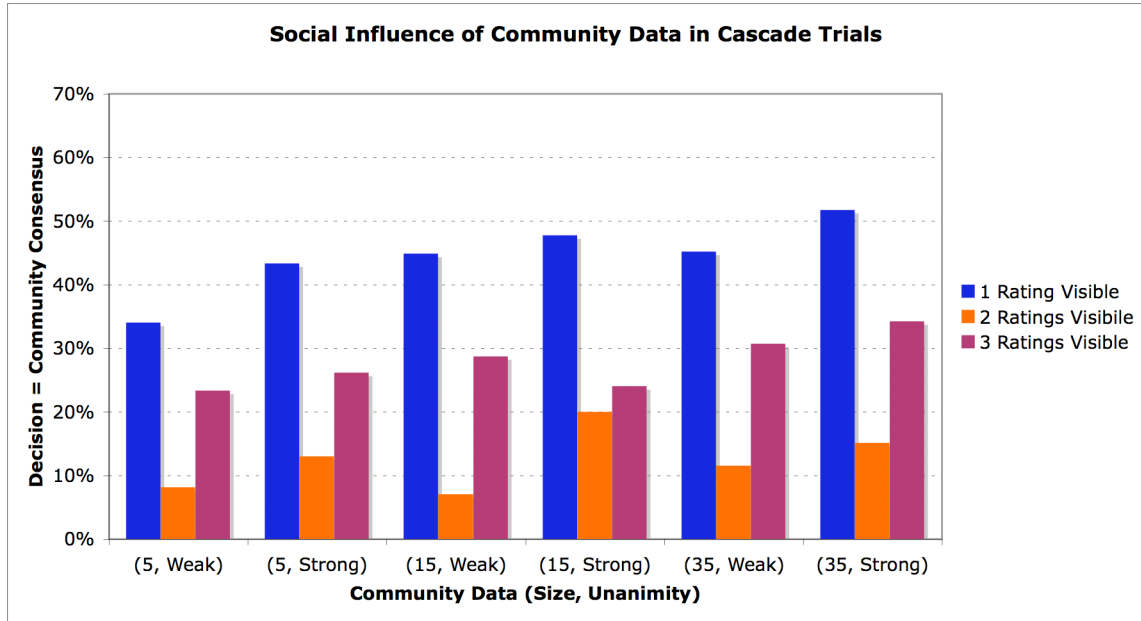
Hypothesis 1 states that community data from the social navigation system exerted informational influence on users. To verify this hypothesis, it is necessary to demonstrate that:

- a. participants' use of community data is high when they see few ratings;
- b. participants' use of community data is low when they see many ratings;

In other words, use of community data inversely correlates with the number of ratings that a participant sees. This inverse correlation would show that participants are drawing information from the community data when they can see fewer ratings and thus have less information.

Figure 7.2 shows the community data's social influence for the cascade conditions. In this chart and for all charts in this chapter, the data is color-coded to denote the number of ratings visible to a participant when he made a decision; blue denotes one visible rating, orange denotes two visible ratings, and purple

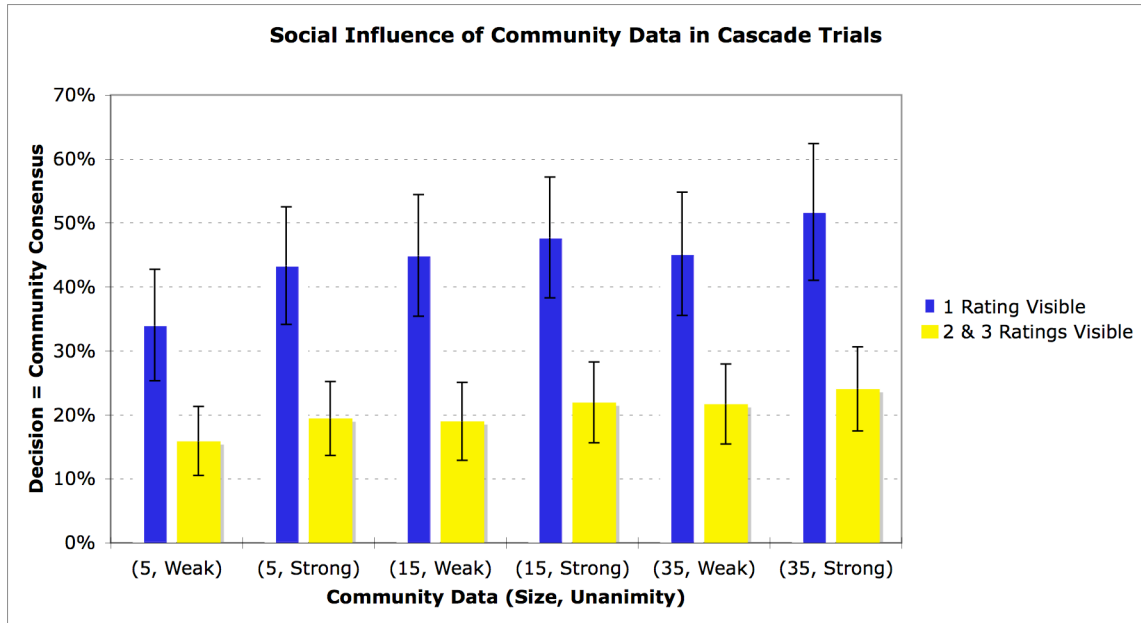




**Figure 7.2** Comparing social influence in cascade conditions when one, two, or three rating are visible.

denotes three visible ratings. Figure 7.2 graphs the community data's size and unanimity against the community data's social influence.

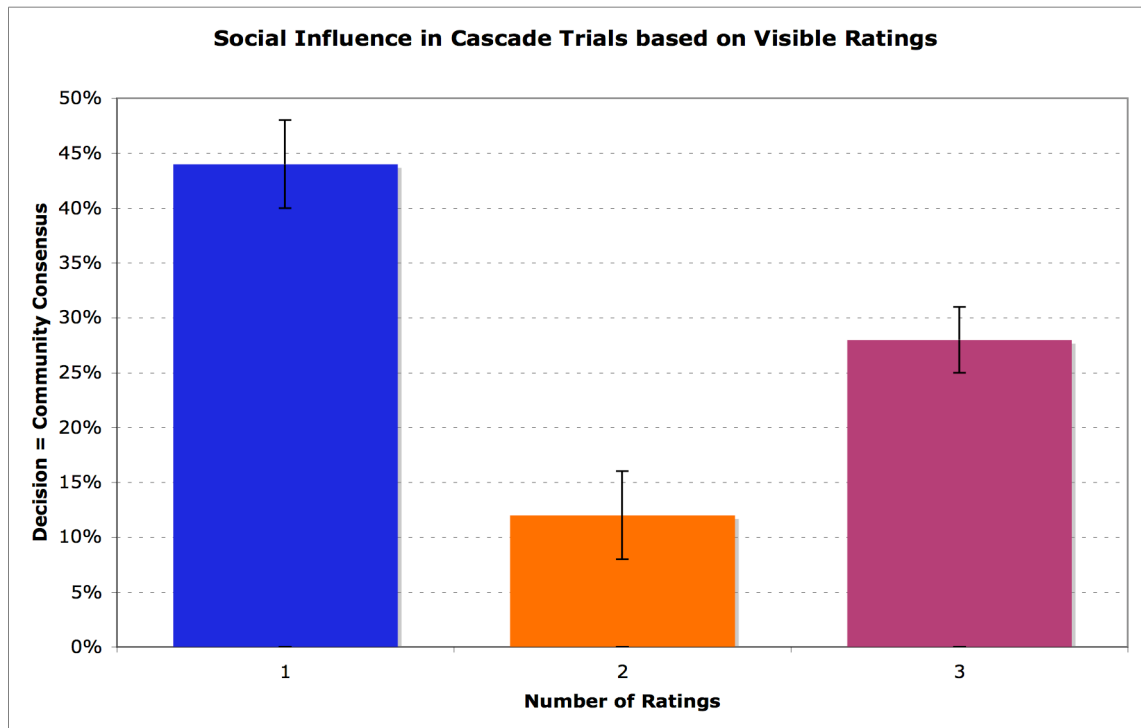
An immediate trend is visible from this data: the community data's social influence is strongest when one rating is visible, is weakest when two ratings are visible, and is moderately weak when three ratings are visible. To further simplify analysis of this data and derive significant results, it is useful to aggregate the decision data into two conditions: (a) one visible rating and (b) 2 or 3 visible ratings. Clustering conditions into a few distinct categories is common in social influence experiments (Baron et al., 1996; Bond & Smith, 1996), and Figure 7.3 shows the data clustered into these two conditions. In this and other charts in this chapter, yellow denotes decision data when either two or three ratings are visible.



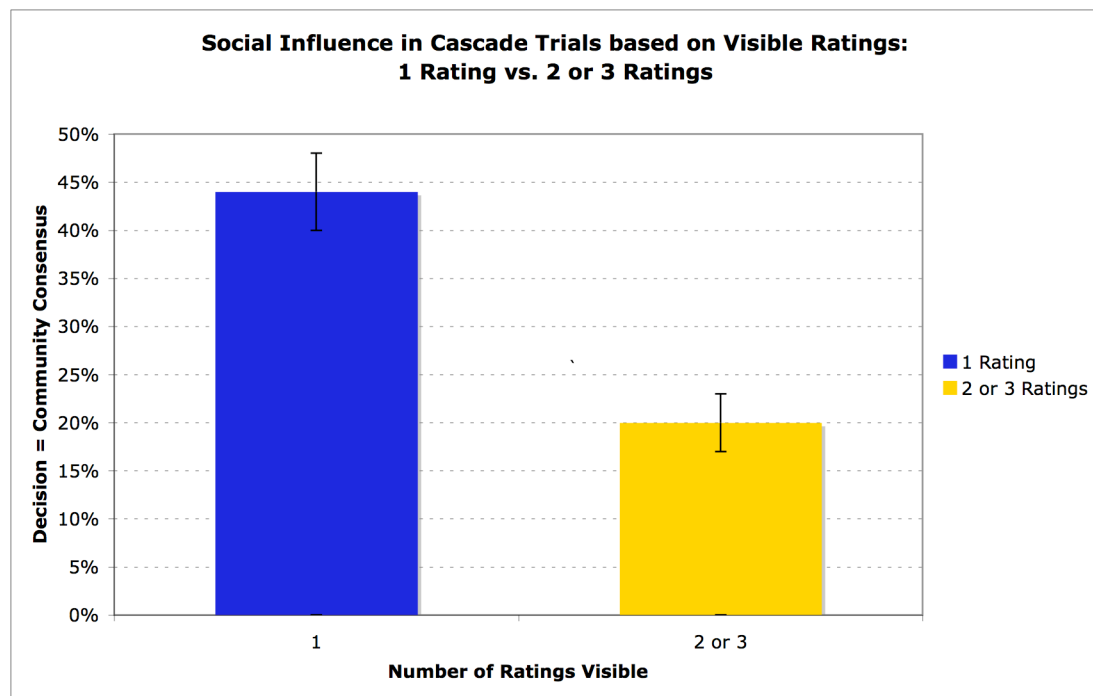
**Figure 7.3** Comparing social influence in cascade conditions when one rating is visible and when two or three ratings are visible. Results show that social influence—making decisions that agree with the community consensus and disagree with rating(s) seen—is stronger when only one rating is visible as compared to when two or three ratings are visible. Error bars denote 95% confidence interval.

Figure 7.3 shows that (a) when participants saw only one rating and hence had less information, they more often made a decision that aligns with the community consensus; and (b) when participants saw two or three ratings and hence had more information, they more often made a decision that aligns with the ratings that they saw. Participants' use of community data, then, is inversely proportional to the amount of other information—watchdog ratings—that they had; in effect, the community data was perceived to be a substitute for watchdog ratings. Based on this data, I conclude that participants used the community data as a form of information, and hence Hypothesis 1 is confirmed: the community data exerted informational influence on participants.

Figures 7.4 and 7.5 aggregate the decision data based on the number of visible ratings to make the inverse correlation between social influence and visible ratings even clearer.



**Figure 7.4** Comparing social influence in cascade conditions when one, two, or three ratings are visible.



**Figure 7.5** Comparing social influence in cascade conditions when one rating is visible vs. 2 or 3 ratings are visible.

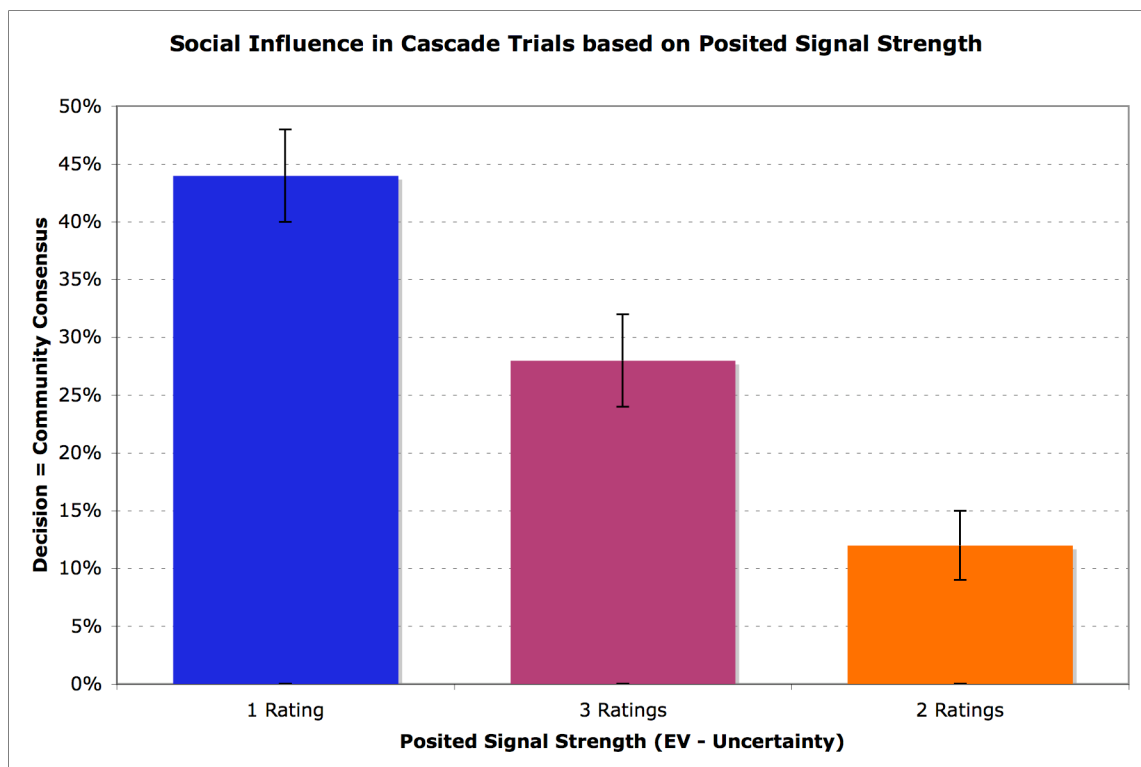
Figure 7.4 is analogous to Figure 7.2, and Figure 7.5 is analogous to Figure 7.3. Figure 7.4 shows the same general trend noted in Figure 7.2: social influence is strongest when one rating is visible, is weakest when two ratings are visible, and is moderate when three ratings are visible. Figure 7.5 confirms the hypothesis that community data exerted informational influence on participants and also shows that this hypothesis holds independent of the size and unanimity of community data.

However, characterizing the social influence of the community data as informational influence does not account for the observation that social influence was stronger in conditions where three ratings were visible as compared to conditions where two ratings were visible. This unexpected observation suggests that another factor, rather than the number of visible ratings and informational influence, is needed to explain these results. I posit that this factor is *uncertainty*, and I posit that there are two causes that can bring about uncertainty in participants: (i) uncertainty may arise when some ratings are hidden and (ii) uncertainty may arise when watchdog ratings disagree with each other.

Using the concept of *signal strength*, it is possible to evaluate the impact of uncertainty on a set of ratings; the signal strength of a set of ratings is how strongly the ratings suggest a particular decision. Surprisingly, the first cause of uncertainty likely *increases* the signal strength for two visible ratings. When two ratings are visible and agree, there are two potential outcomes based on the value for the final, hidden rating: (1) the third rating agrees with the two visible ratings or (2) the third rating disagrees, which is equivalent to the scenarios in which three ratings are visible. Thus, at worst two ratings provide the same signal strength as the three ratings, and at best they provide more. Hence, I argue that two ratings have a stronger signal strength than three ratings. The second cause of uncertainty—when ratings disagree—likely weakens the signal strength of

three visible ratings because the disagreement in ratings can create doubt in participants' minds about the ratings, the watchdogs' competence, or the nonprofit.

Regardless of the uncertainty's cause, positing that the signal strength of two ratings is stronger than the signal strength of three ratings can account for these results. Figure 7.6 shows a comparison of informational influence compared to posited signal strength, and this comparison yields a strong inverse correlation between informational influence and the ratings' signal strength. More investigation is needed to confirm this conjecture.



**Figure 7.6** Social influence in cascade conditions organized by the posited signal strength for each set of ratings. Posited signal strength includes both the expected value of a set of ratings and the uncertainty associated with the ratings.

### **7.3.2 Finding: Herding in a Social Navigation System can be Characterized as Informational Cascades**

Hypothesis 3 argues that the herding in social navigation systems can be characterized as informational cascades. Two criteria must be met to argue for this hypothesis. First, participants must exhibit cascade behavior; in other words, individuals must ignore their own, private information and instead make a decision that agrees with the community consensus. In this experiment, the private information is the watchdog ratings that participants can see; cascade behavior, then, occurs when participants make a decision that agrees with the community data and disagrees with the watchdog ratings that they see. The second criterion that must be met in order to characterize herding behavior as a cascade is that the decision to herd—to ignore private information and go with the community’s decision—must be driven by informational influence.

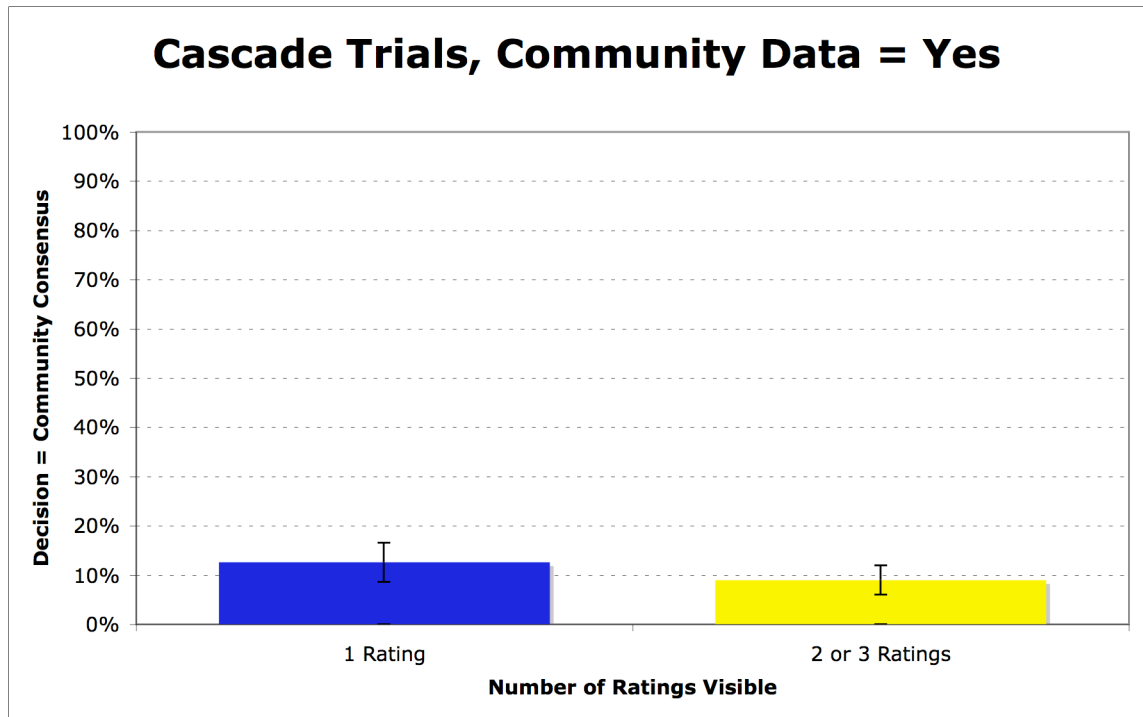
The data, graphs, and discussion in the previous section provide evidence to support these criteria and hence this hypothesis. Recall that all the decision data in Figures 7.2, 7.3, 7.4, and 7.5 derive from conditions in which the watchdog ratings suggested a different decision than the community data. These conditions, then, provided the opportunity for participants to engage in cascade behavior—to make a decision that agrees with the community despite seeing watchdog ratings that suggest the other decision. Figures 7.2, 7.3, 7.4, and 7.5 show that participants often engaged in cascade behavior in all cascade conditions, even when two or three ratings were visible. The previous section also presents substantial evidence that participants’ herding behavior was driven by informational influence.

Thus, analyses of the decision data in the cascades conditions indicate that informational cascades can and do occur in social navigation systems and that

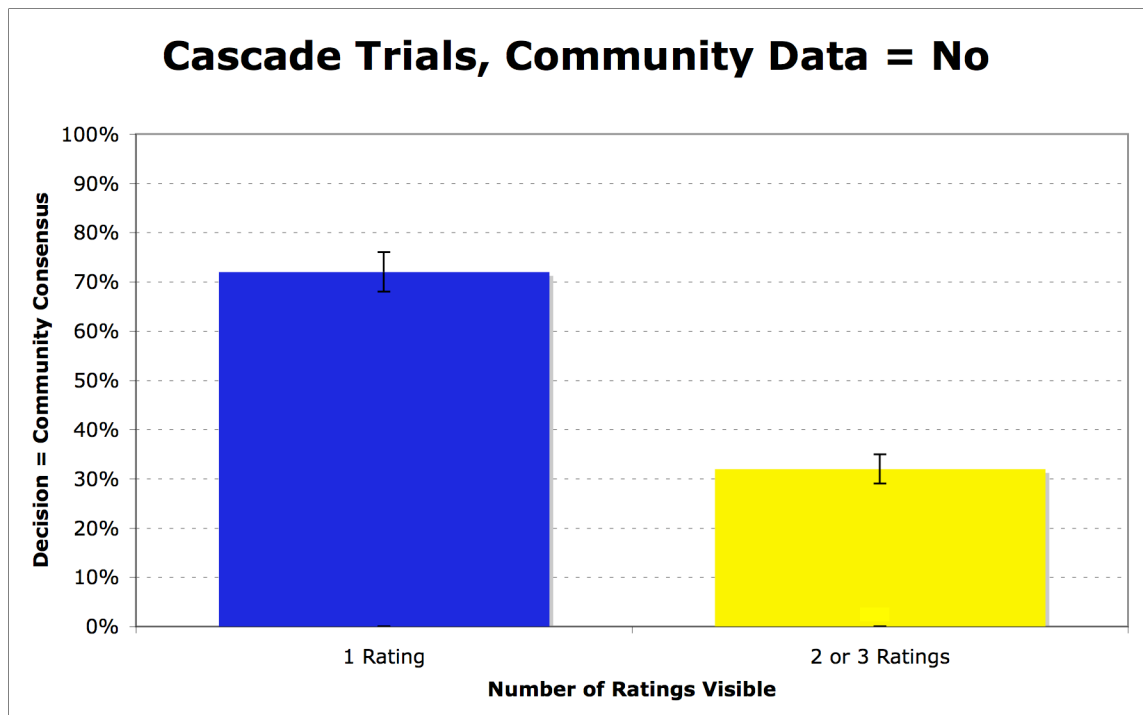
the herding in social navigation systems can be characterized as informational cascades.

### **7.3.3 Community Data's Social Influence Reinforces Bias but does not Overcome It**

Figure 7.7 presents decision data for cascade conditions in which the community data suggests a *Yes* decision and the watchdog ratings suggest *No*, and Figure 7.8 presents decision data for conditions in which the community data suggests *No* and watchdog ratings suggest *Yes*.



**Figure 7.7** Decision data for cascade trials when community data suggests *Yes* and ratings suggest *No*.



**Figure 7.8** Decision data for cascade trials when community data suggests *No* and ratings suggest *Yes*.



The decision data in these figures are striking. The data indicates that the community data's social influence decreased markedly when the community data suggested a *Yes* decision as compared to when it suggested a *No* decision. For conditions where the community data suggests *Yes*, there is not a significant difference in social influence between the conditions with one visible rating and the conditions with two or three visible ratings. The data, however, is still trending such that it is likely that social influence is stronger in conditions with one visible rating and compared to conditions with two or three visible ratings. Taken together, there is substantial evidence that community data exerts informational influence regardless of whether the community data suggests *Yes* or *No*, but the direction of the community data markedly changes the strength of the community data's influence.

It is not immediately clear how to interpret these observations because similar results have not been found in other social influence or informational cascade experiments. The most straightforward explanation is that these results may arise due to participants' strong bias toward answering *No* and strong bias against answering *Yes* (see Section 7.1.2). In other words, participants may have been skeptical of making a *Yes* decision. Positing that participants were skeptical or biased against answering *Yes*, the social influence that community data exerts toward a *No* choice may indicate that community data reinforces or promotes participants' bias. On the other hand, the very weak social influence that community data exerts toward a *Yes* answer may indicate that community data does not overcome participants' bias.

These results indicate that the final impact of a social navigation system is the product of both the influence a system exerts on users and biases or preferences that users bring to the decision making process. Consequently, a system's influence cannot be understood without appreciating the impact of each of these

factors, and care should be taken to measure the effect of a system’s community data for each choice that a user has in order to separate the influence of a system and the influence of biases or preferences. If there is a default, cost-free choice, these results indicate the community data may influence users markedly toward that choice as compared to other choice. In summary, then, this decision data suggests that a system’s community data may interact with characteristics of the decision that users are making—such as the presence of a default decision—and this interaction may affect users’ final decisions in unexpected ways.

#### 7.3.4 Analyzing the Impact of Community Data’s Size and Unanimity

Hypotheses 4 and 5 state that as the size and unanimity of the community data increase the social influence that the community data exerts. However, decision data from the cascade conditions presents a more complex picture. Table 7.2 presents statistical significance values that depict main effects for the three independent variables—ratings configuration, community data size, and community data unanimity—on the community data’s social influence. The table presents significance values for three condition sets: all cascade conditions, cascade conditions in which the community data suggests *Yes* and the ratings suggest *No*, and cascade conditions in which the community data suggests *No* and the ratings suggest *Yes*.

The data in Table 7.2 is compelling. The strong main effect of the ratings

**Table 7.2** Significance values for decision data from cascade conditions for ratings configuration and community data size and strength.

	<b>Ratings Configuration</b>	<b>Com. Data Size</b>	<b>Com. Data Strength</b>
<b>All Cascade Conditions</b>	$p < 0.00001$	$p < 0.05$	$p < 0.08$
<b>Cascade Conditions: CD Yes, ratings No</b>	$p < 0.001$	---	$p < 0.01$
<b>Cascade Conditions: CD No, ratings Yes</b>	$p < 0.00001$	---	$p < 0.03$

configuration on social influence is to be expected given community data exerted informational influence on participants.

However, the main effect for community data's size and unanimity is relatively weak. The size of the community data had a main effect ( $p < 0.05$ ) on participants' decisions across all cascade conditions but did not have a main effect for either subset of conditions. The community data's size had a main effect in the set of all cascade conditions when comparing the small size (5 people) to the large size (35 people); no effect was found between small and medium size nor between medium and large size. Given that there was a main effect of the size overall, it is likely that the number of conditions in the subsets prevented the community data's size from yielding a main effect in these subsets. Additional conditions may confirm that size yields a main effect on the community data's social influence for each of the subsets of conditions as well.

The main effect of the community data's unanimity shows an interesting pattern. The main effect overall is quite weak and could even be considered insignificant. However, the significance is much stronger in each of the subsets, and the strongest significance occurs in the cascade conditions set where the community data suggests a *Yes* decision and the ratings suggest *No*. These findings complement the previous discussion about the impact of community data on participants' skepticism.

No main effect on social influence was found for either the size or unanimity of community data for particular rating conditions, but the trends within some conditions suggested that a larger number of trials could yield an effect.

#### **7.4 Analysis of Decision Data from Non-Cascade Conditions**

In non-cascade conditions, the watchdog ratings and community data agree and suggest the same choice. The three conditions that comprise the non-cascade

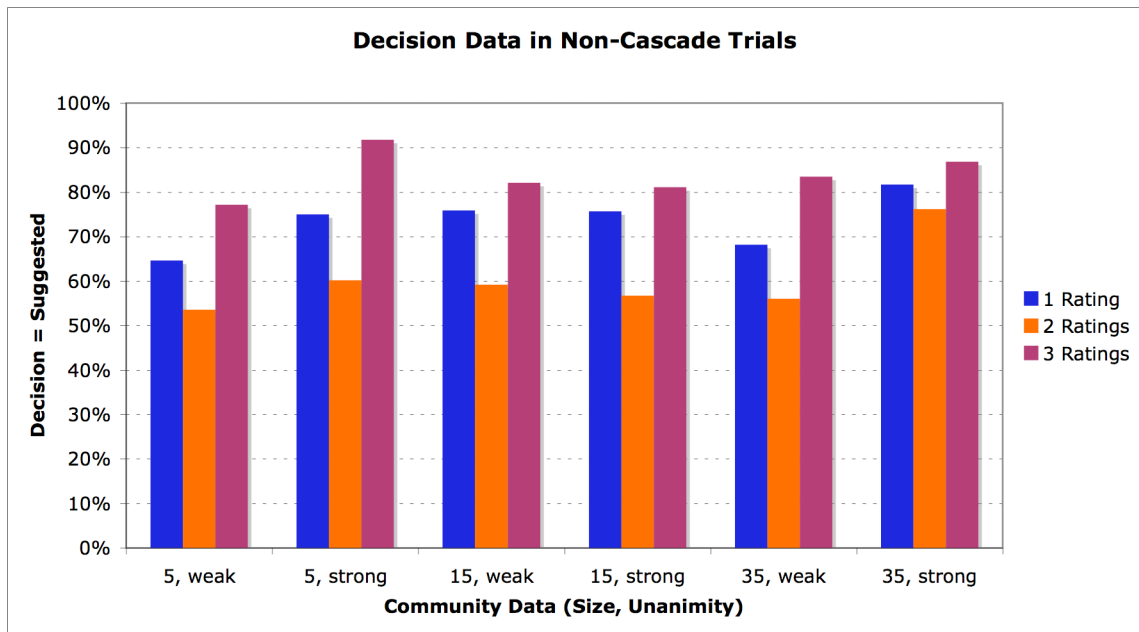
conditions are (A) three ratings visible: two ratings are the same and the third rating differs; (B) two ratings are visible and are assigned different values; and (C) one rating is visible. In conditions A and C, the community data agrees with the ratings, and in condition B, the ratings are neutral and the community data is randomly assigned a direction.

I employ a different metric to investigate decision data from non-cascade conditions as compared to the metric I used to investigate cascade conditions. The principal metric that I employ for non-cascade conditions is how often participants' made a decision that agreed with the suggested choice. I refer the suggested choice as the *expected* choice, and I refer to the other choice as the *unexpected* choice.

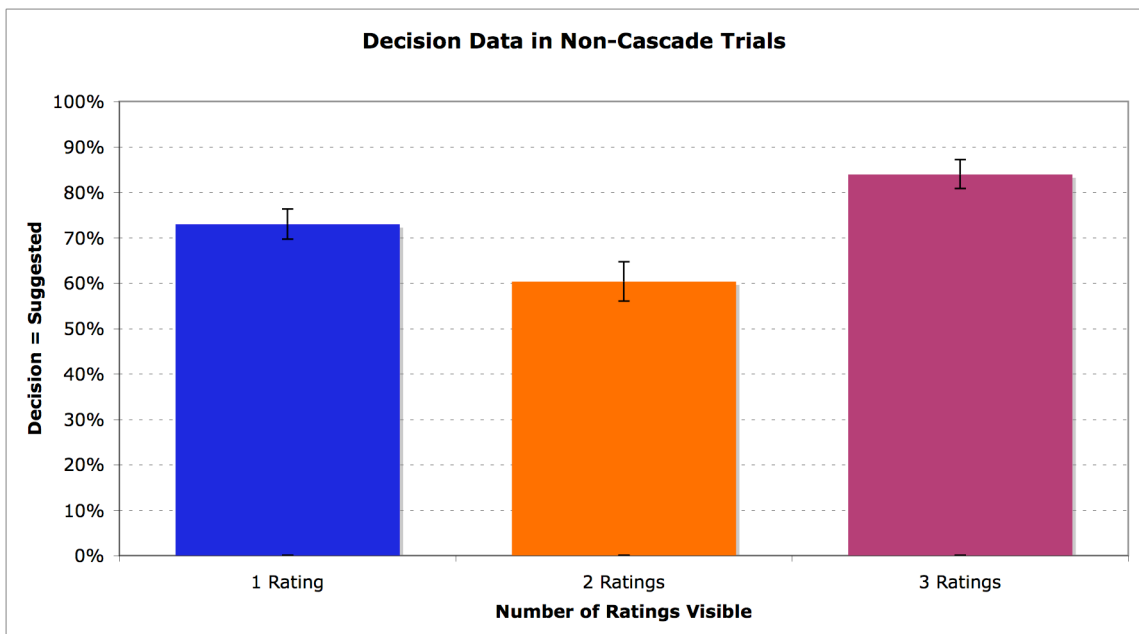
My analysis of the decision data from non-cascade conditions parallels my analysis for the cascade conditions. I first discuss trends in the data based on the number of visible ratings. Next, I discuss differences between conditions in which the suggested decision is *Yes* and conditions in which the suggested decision is *No*. Finally, I discuss the impact of the community data's size and unanimity on decisions made in non-cascade conditions.

#### **7.4.1 Findings: Social Influence Strength and Egocentric Discounting**

Figure 7.9 shows the decision data for non-cascade conditions, and Figure 7.10 shows the decision data aggregated by the number of ratings that participants saw. There is a clear and significant trend in the data: participants make the expected decision—the decision that the ratings and the community data suggest—most often in condition A, when they saw all three ratings. In addition, participants made the expected decision more often in condition C, when they saw a single rating than in condition B, when they saw two split ratings.



**Figure 7.9** Social influence in conditions when one, two, or three watchdog ratings are visible and the ratings suggest the same decision as the community data. When two ratings are visible, they are split and the direction of the community data is assigned randomly; when three ratings are visible, the ratio is always two in one direction and one in the opposite direction.



**Figure 7.10** Social influence across conditions when one, two, or three watchdog ratings are visible and the ratings suggest the same decision as the community data. Influence is measured across community data sizes and strengths.

Decision data for condition B, where two ratings are visible but are different, offers a unique and clear measurement of the social influence that the community data exerted on participants. Because the ratings were split, they offered no guidance for a decision, and thus participants likely based their decision on the community data. Overall, participants chose the expected decision in 60% of the conditions for condition B, and thus the social influence of community data is, on average, about 10%.

It is useful to compare decision data from condition A, where participants saw a single rating, with decision data from conditions B and C. Participants chose the suggested answer 13% more often in condition A than they did in condition B, and 25% more often in condition C than in condition B.

These decision data indicate that, because the community data and rating suggest the same decision, they are additive in strength, and previous research of social influence in nonprofit giving employs an additive perspective for multiple information sources as well (Croson & Shang, 2008). From an additive perspective, decision data from condition B is the sum of social influence and a single rating, and condition C is the sum of social influence and two ratings. Based on this analysis, the strength of a single rating is about 13%. This can be verified because the difference between conditions A and B and between B and C is a single rating; in both instances, the percentage of difference is about 13%.

In summary, the strength of the community data's social influence is about 10% and the strength of a single rating is about 13%. This data supports Hypothesis 2: participants engaged in egocentric discounting, valuing a single rating more highly than the totality of the community data. Of course, it follows that participants valued a set of ratings more highly than the community data as well.

Decision data from the non-cascade conditions can provide insight into the data that might be expected from control conditions in which participants saw only watchdog ratings. Because a single rating exerted about 13% influence on participants' decisions, it is expected that participants would choose the suggested answer in about 63% of the trials in which a single rating is visible. Similarly, because a set of three ratings with a 2 to 1 ratio exerted about 26% influence on participants' decisions, it is expected that participants would choose the suggested answer in about 76% of the trials in which three ratings are visible. Lastly, for a condition in which two ratings are visible and agree, it is expected that participants would choose the suggested answer in more than 76% of the trials.

Further support for these predicted decision data in control conditions can be found from the cascade trials' decision data. In particular, recall that the signal strength of one, two, and three ratings is discussed and that the decision data suggests that the signal strength of one rating is weakest, the strength of two ratings that agree is strongest, and the strength of three ratings with a 2-1 ratio is moderately strong. These relative signal strengths match both the decision data in the non-cascade conditions and the predicted decision data for the control conditions.

Hence, decision data in both the cascade and non-cascade trials indicates that the sets of ratings used in this experiment can be ordered ordinally. In particular, the data shows that the strength of rating sets, from strongest to weakest, is:

- i. two ratings, ratio 2-0 (ratings agree);
- ii. three ratings, ratio 2-1 (two ratings agree, one disagrees);
- iii. one rating, ratio 1-0;
- iv. two ratings, ratio 1-1 (ratings disagree).

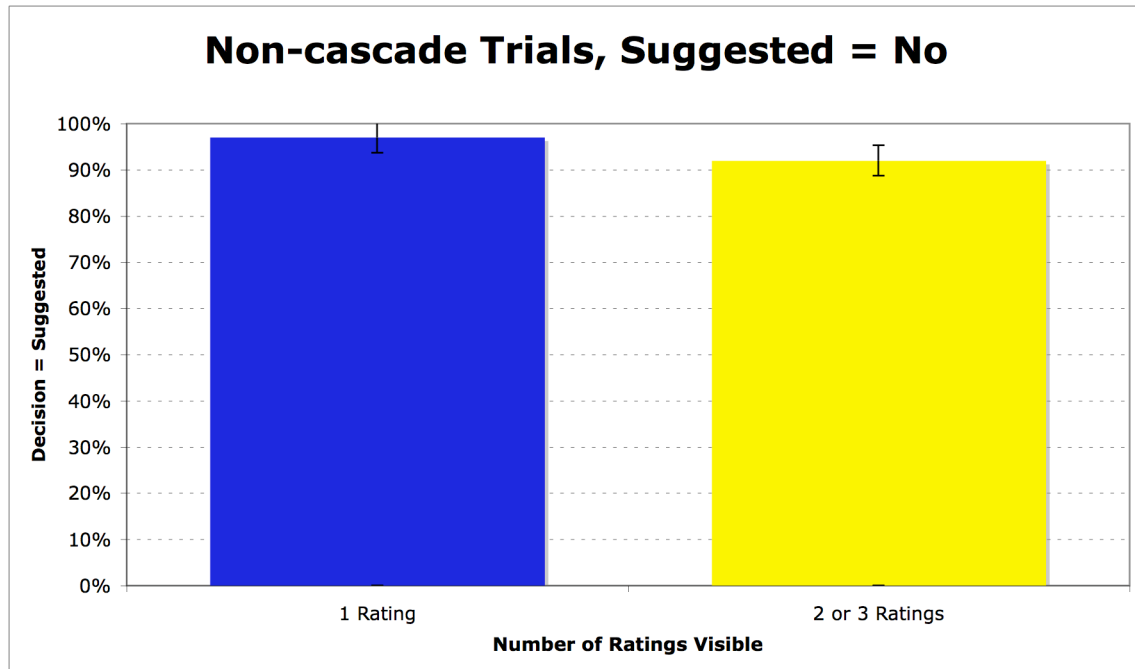
Because ordinality amongst sets is likely a function of information, ordinality amongst rating sets provides a means to compare information content across rating sets without knowing the information content of particular ratings. Ordinality, then, reduces the need for collecting decision data from traditional control conditions but provides hypotheses should control conditions be studied.

Lastly, by ordering ratings sets ordinally based on their influence on users' decisions, it is possible to foster a relationship between set ordinality and the strength of the community's data social influence. This relationship provides another perspective from which to argue that community data exerts informational influence rather than normative influence. The decision data from the cascade trials show that the community data's social influence increases as the rating sets' ordinality decreases. Because ordinality is likely based on information content, Figure 7.6 can be interpreted as the relationship between the community data's social influence and the rating sets' ordinality. Figure 7.6, then, shows that the more information/influence a ratings set contains/exerts, the less influence the community data has. This is another perspective by which to establish informational influence of community data.

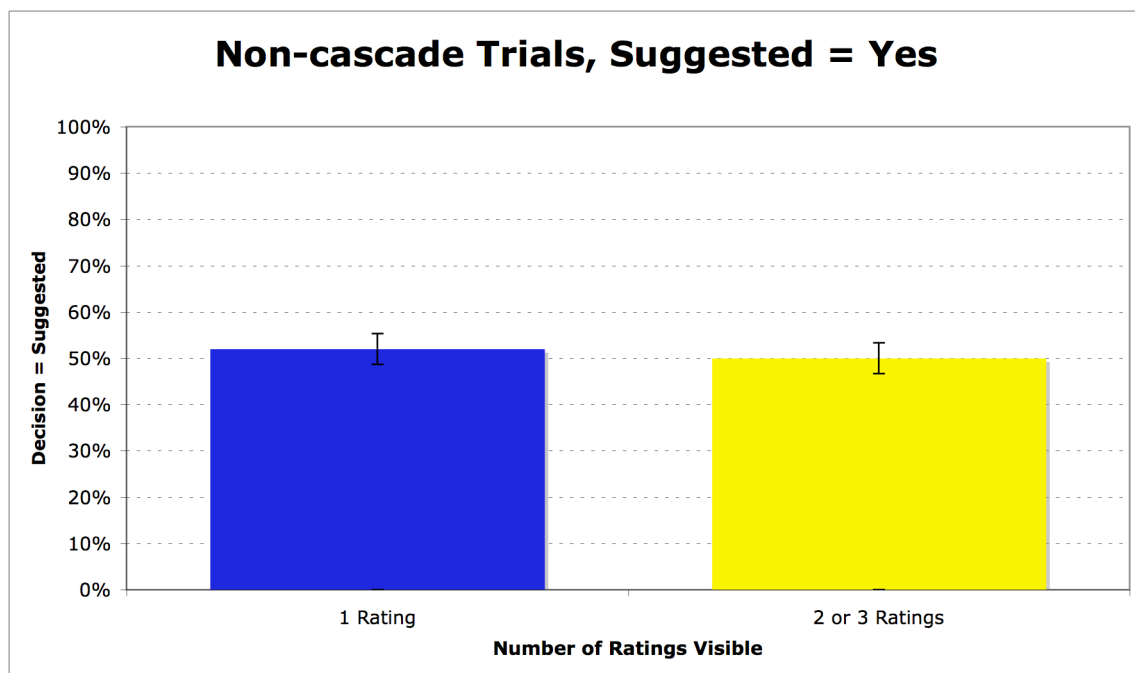
#### **7.4.2 Differences between Suggesting *Yes* and Suggesting *No***

Figures 7.11 and 7.12 show decision data for the non-cascade conditions when the suggested decision was *Yes* and when the suggested decision was *No*. Figures 7.13 and 7.14 show the decision data broken down by community size and unanimity as well as condition. As was true in the cascade conditions, participants provided significantly different answers depending on the suggested choice.

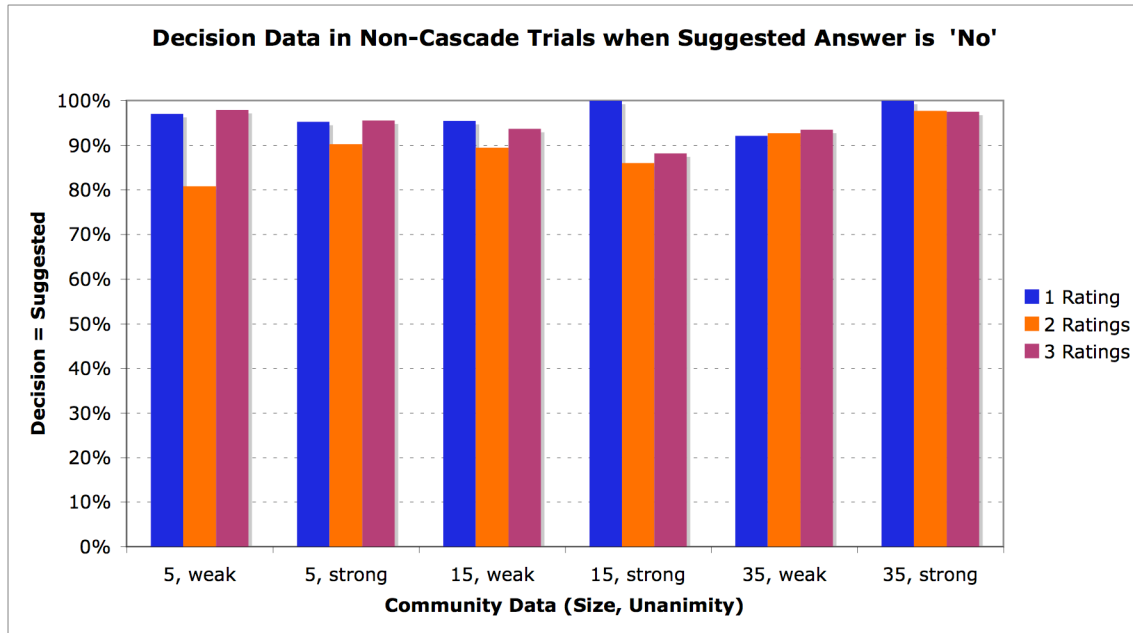




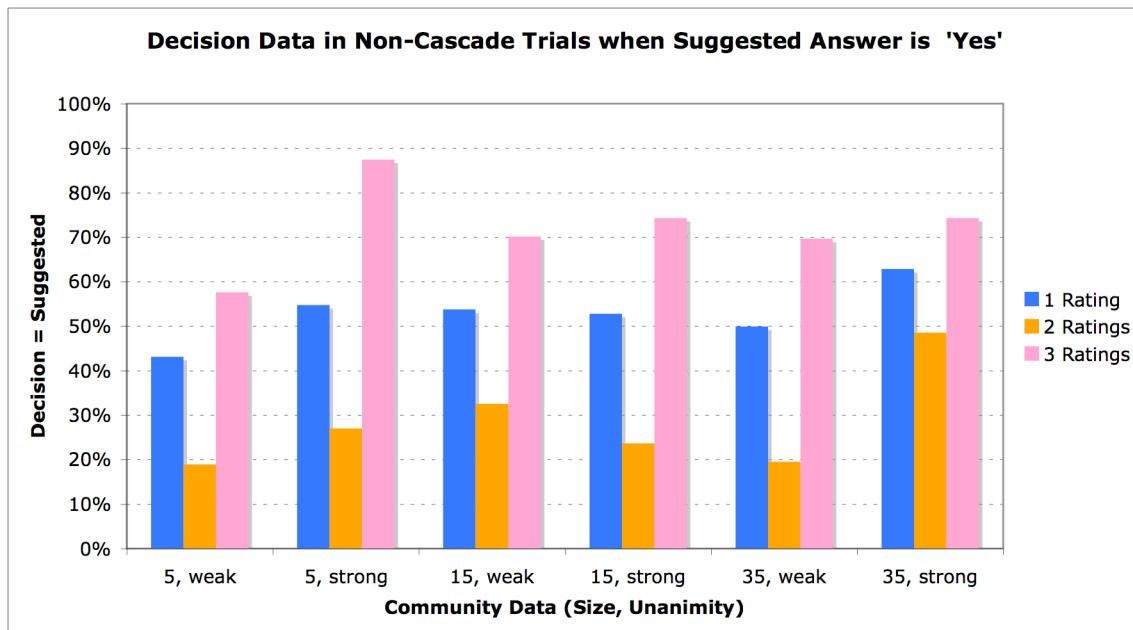
**Figure 7.11** Decision data for non-cascade conditions when expected decision is *No*.



**Figure 7.12** Decision data for non-cascade conditions when expected decision is *Yes*.



**Figure 7.13** Decision data based on community data size and unanimity for non-cascade conditions when expected decision is *No*.



**Figure 7.14** Decision data based on community data size and unanimity for non-cascade conditions when expected decision is *Yes*.

Figure 7.11 shows that participants nearly always follow the suggested decision when the suggestion is *No* regardless of the condition. This data provides additional evidence that the domain and decision structure for this experiment substantially impact the decision data. Because participants' are so strongly biased toward choosing *No*, any data that reinforces this bias overwhelmingly leads to decisions of *No*. What is particularly interesting about the conditions in which the data suggests a *No* decision is that the community data's size and unanimity exert no significant effect because the data is so overwhelmingly skewed toward *No* decisions. Hence, Figures 7.11 and 7.13 are striking in their uniformity.

Figures 7.12 and 7.14 show that nearly all of the differences between the non-cascade conditions arise from conditions in which the suggested decision is *Yes*. That is, the overall trend in the decision data for non-cascade conditions—participants are most likely to choose the suggested answer when they see three ratings or, slightly less so, when they a single rating, but participants are much less likely to choose the suggested answer when they see two ratings that disagree—is apparent in the decision data for conditions in which the suggested choice is *Yes* but not for conditions in which the suggested choice is *No*.

#### **7.4.3 Analyzing the of Impact of Community Data's Size and Unanimity**

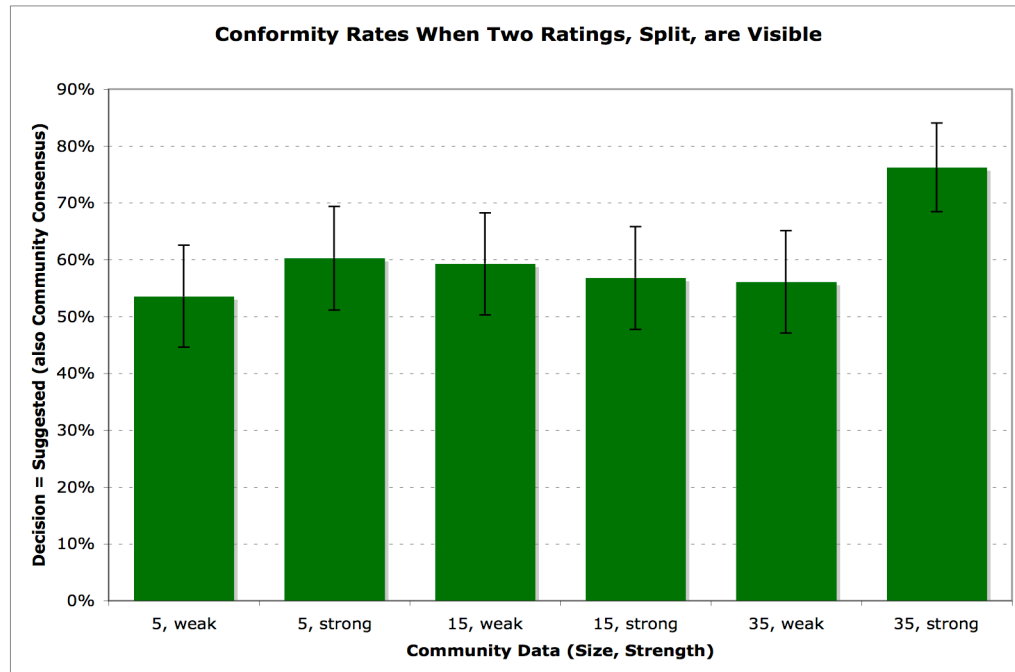
Table 7.3 provides statistical significance values for the ratings configuration, the size of community data, and the unanimity of community data for the three condition sets discussed: all non-cascade conditions, non-cascade conditions when the suggested answer was *Yes*, and non-cascade conditions when the suggested answer was *No*. As was true for cascade trials, community data unanimity exerted a much stronger effect on participants' decisions than did

**Table 7.3** ANOVA analysis of factors for non-cascade conditions.

	<b>Ratings Configuration</b>	<b>Size</b>	<b>Strength</b>	<b>Interactions</b>
<b>All Noncascade Conditions</b>	$p < 0.00001$	---	$p < .003$	size & strength: $p < 0.05$
<b>Noncascade Conditions: Suggested Answer Yes</b>	$p < 0.00001$	---	$p < 0.1$	size & strength: $p < 0.05$
<b>Noncascade Conditions: Suggested Answer No</b>	$p < 0.01$	---	---	

community data size. In fact, community data size did not exert a significant effect on participants' decisions. Community data unanimity exerted a main effect on all non-cascade conditions and conditions where the suggested answer was *Yes*.

Finally, there is a slight interaction effect between the size and unanimity of the community data (Figure 7.15) for these two condition sets as well. This is a compelling finding as it suggests that size and unanimity are not independent.



**Figure 7.15** Rates of conformity when participants saw two ratings, each of which had a different value. Interaction effect occurs when both community data size and unanimity are high. Interaction effect significance is  $p < 0.03$ , error bars are  $p < 0.1$

## 7.5 Summary

The decision data from this experiment provided varying levels of support for my hypotheses about the social navigation user experience. The data strongly supports Hypotheses 1 and 3: (1) community data exerted informational influence on participants and (2) the herding behavior that arises due to community data is best characterized as informational cascades. In the cascade conditions, when participants saw fewer watchdog ratings, they chose to make a decision that agreed with the community data more often than in conditions when they saw more ratings.

The inverse correlation between the number of ratings seen and the strength of social influence that the community data exerted provides strong evidence that community data exerts informational influence on participants. The cascade

conditions also demonstrated herding behavior—individuals ignoring watchdog ratings that they saw and instead making a decision that agreed with the community data. Because community data exerts informational influence, this herding behavior is best characterized as informational cascade behavior.

Despite these findings, my analysis of the decision data in the cascade conditions indicates that another factor is needed to explain why informational influence is not higher when two ratings are visible as compared to when three ratings are visible. I have argued that participants' uncertainty is the factor that is most likely to explain these observations.

Analysis of the non-cascade decision data provides tentative support for Hypothesis 2, egocentric discounting. The data shows that the social influence of community data led to a 10% increase in participants choosing the suggested answer, the influence of a single rating led to a 13% increase in participants choosing the suggested answer, and the influence of three ratings with a 2:1 ratio led to a 25% increase in participants choosing the suggested answer. While this analysis does not conclusively demonstrate egocentric influence because participants did not make an initial and final guess, it does indicate that participants value their personal information more highly than they value the community data.

Hypotheses 4 and 5, which posit that the size and unanimity of community data correlate with its social influence strength, met with mixed results. Community data size proved to be a significant effect only in the sum of all cascade conditions, and size was not a significant factor in either subset of cascade conditions. Community data unanimity exerted a significant effect in both cascade and non-cascade conditions and in all subsets except when in non-cascade conditions in which the suggested answer is *No*. There was also an

interaction effect between community size and unanimity in non-cascade conditions when the suggested answer was *Yes*.

In general, the factors that influenced participants' decisions most strongly were the agreement or disagreement between the watchdog ratings and community data (cascade vs. non-cascade conditions) and the direction of the community data (in cascade conditions) or the direction of the suggested decision (in non-cascade conditions). Community data unanimity also was a significant factor in participants' decisions. Community data size, however, was a minor or insignificant factor in participants' decisions.

Finally, the experiment's decision data indicates that participants exhibited a bias toward a *No* decision. In cascade conditions, where the ratings and community data suggested different decisions, the data indicates that community data reinforces participants' bias toward answering *No* but does little to help overcome this bias to answer *Yes*. The decision data for non-cascade conditions showed the same pattern as in the cascade conditions, and hence this finding is both strong and robust. This finding demonstrates that a social navigation system's impact on users' decisions is mediated by biases, preferences, and incentives that users bring to the decision making process. Hence, when investigating a system's impact, it is useful to identify and separate the influence of users' biases, preferences, and incentives and the influence of the system.

## CHAPTER 8

### IMPLICATIONS FOR THE DESIGN, USE, AND EVALUATION OF SOCIAL NAVIGATION SYSTEMS

The previous chapters in this thesis have described, discussed, and analyzed the social navigation user experience. This chapter employs the social navigation user experience perspective to discuss improvements to the design, use, and evaluation of social navigation systems.

There are two major foci in this chapter. First, I argue that in domains where people make use of *objective information*—information that is independent of personal preferences—to make decisions, social navigation systems should operate on objective information rather than decisions or opinions. The concept of *social navigation systems for objective information* can improve the design and use of systems by focusing efforts on supporting the capture, aggregation, and representation of knowledge.

Second, I discuss a general evaluation method for social navigation systems that can measure the social influence of a system's community data. This method can be employed to measure and compare the social influence and impact of social navigation systems on users' decisions across systems, domains, and disciplines. There are, however, limitations to this method. The method cannot determine what decisions users are most likely to encounter and, consequently, what type of impact a social navigation system is most likely to have on users' decisions.



## 8.1 Improving the Design of Social Navigation Systems

Findings from the nonprofit choice experiment (Chapter 7) show that community data exerts informational influence on users when they make decisions. That is, users perceive community data as a source of knowledge or information. This perspective can be applied to understand (a) how the use of social navigation systems differs between subjective and objective domains and (b) how social navigation systems can better support users' decisions by focusing on information rather than decisions.

### 8.1.1 Social Navigation Systems for Subjective and Objective Domains

Traditionally, social navigation systems have been applied to domains such as music, movies, recipes, and books. These are *taste-based* or *subjective domains*, and the defining characteristic of these domains is that users make decisions based on personal preferences. Personal preferences have two very compelling qualities. First, everyone has preferences, and those preferences can never be wrong. Second, it is easy for an individual to understand what others know when they hold a preference for an item; that is not to say that an individual understands exactly *why* other people hold a preference, but that she can empathize with what it is like to hold that preference because she too has preferences for similar items.

In contrast, *objective domains* are domains where users employ objective information as well as other information sources. *Objective information* is information that is independent of personal preferences and thus can be agreed upon by multiple people regardless of their preferences. Examples of objective domains include security management, finances, and health. Consider an example from the security management domain: a particular software application produces unwanted popup windows when browsing the Internet, and hence it is

malware. This information—that a software application is spyware—is an instance of objective information because it is true regardless of personal preferences. In the nonprofit choice experiment, the experiment’s structure framed watchdog ratings as objective information as well; regardless of a participant’s personal preferences, a watchdog’s rating was constant.

Two factors complicate conceptualization of objective domains. First, individuals often interpret objective information by applying their personal preferences to interpret the information. Hence, the impact of watchdog ratings differed among participants in the nonprofit choice experiment; some participants chose *No* whenever they saw a low rating, but others chose *No* only if they believed that the majority of ratings were low. Another complicating factor about objective information is that it can change. The potential plasticity of objective information was not addressed in the nonprofit choice experiment, but it is a complicating factor in conceptualizing objective information. For instance, nutritional and health information is under constant revision, yet at any particular point in time, the current information is considered to be “correct.”

Social navigation systems have been applied much less often to objective domains. Acumen and Bonfire are early examples of how social navigation systems can be applied to objective domains. Recently, social navigation systems have been introduced to other objective domains. For instance, WebMD<sup>26</sup> now enables users to rate and review prescription drugs.

There is clearly a need, then, to better understand how social navigation systems can support user decision making in objective domains. Based on my work with Acumen and Bonfire and findings from the nonprofit experiment,

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<sup>26</sup> <http://www.webmd.com/>

social navigation systems applied to objective domains should focus on the capture, aggregation, and representation of objective information. While these foci may also be useful to consider when applying social navigation systems to subjective domains, they are likely less important in subjective domains. I discuss these foci in the following section.

### **8.1.2 Social Navigation Systems for Objective Information**

I have argued that, in an objective domain, a social navigation system should aggregate objective information rather than personal opinions. Social navigation systems for information are distinct from social navigation for opinions in many ways; one important difference is that social navigation systems for information pose unique challenges in areas of capturing, personalizing and representing information to support decision making.

Recall that a key difference between personal preferences and objective information is that individuals always possess preferences but do not always possess information. Moreover, users employ personal preferences when making decisions in taste-based domains, but individuals do not always employ knowledge or information when making decisions in objective domains. As demonstrated in the nonprofit experiment, individuals often ignore information they have access to—watchdog ratings—and follow the community consensus instead.

This behavior causes considerable problems in social navigation systems. Users lacking information or who are unsure of information they have access to often use community data for guidance. Naturally, uncertain users frequently choose to follow the community consensus, and their decision is added to the system's community data. However, subsequent users viewing the community data often assume the data derives from users that have employed information to

make decisions rather than users who have followed the community consensus. If enough users misinterpret community data this way, an informational cascade forms. Informational cascades lead to a false majority within a social navigation system, and the system's community data does not accurately reflect the community's knowledge. Cascades, of course, can persist for some time and can lead users to many suboptimal decisions.

Based on this behavior, the first challenge for a social navigation system applied to an objective domain is to distinguish between the capture of objective information and the capture of decisions. Due to informational influence and cascades, the objective information that a system captures can be markedly different than the decisions that it captures. Capturing information is more valuable than capturing decisions; captured information helps individuals make more informed decisions whereas captured decisions can lead users to many different choices, some of which are informed and others of which are misinformed<sup>27</sup>.

After a social navigation system captures objective information, the next step is to aggregate that information. In taste-based domains, many social navigation systems use a collaborative filtering (CF) algorithm (Resnick et al., 1994) to provide personalized output. Because social navigation systems in taste-based domains attempt to produce output that matches users' personal preferences as closely as possible, a personalization algorithm is ideal because data that arises

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<sup>27</sup> There is, however, a caveat: there are instances in which others' decisions, regardless of whether they are based on knowledge or not, are valuable information for individuals making their own decision. When there are shared resources at stake—such as in instances when a tragedy of the commons (Hardin, 1968) might occur—or one's use of a item impacts another use of a similar item [i.e. the “network effect” (Uzzi, 1996)], then one's decision may well depend on the decisions of others rather than the knowledge of others.

from other people with preferences dissimilar to an individual's preferences can often be ignored.

However, it is not at all clear that personalizing information based on an individual's preferences is advantageous for supporting decisions in objective domains. A personalization algorithm aggregates community data so as to skew it towards a user's interests, but many difficulties arise when attempting to personalize objective information that do not arise when personalizing preferences. It is not clear that objective information—which I have defined to be independent of users' preferences—should be personalized based on a users' preferences. Information can be valuable if it runs counter to a user's preferences, and in fact may be quite valuable in such instances because it can prompt a user to reevaluate his preferences. Employing personalization algorithms on captured information also runs the risk of the algorithms ignoring some information and emphasizing other information too much, and it is unclear how often a personalization algorithm can emphasize and cull objective information to match a user's needs.

In addition, a personalization algorithm for objective information may have to enable users to understand what information was aggregated, how it was aggregated, and how it be disaggregated in the event that a user wants to see the original information or determine whether the personalization process matches the method she would prefer to use to aggregate the information.

The final challenge of a social navigation system is credibly representing user information and knowledge in the community data. In the nonprofit choice experiment, some of the difficulty in overcoming participants' skepticism and getting them to answer *Yes* can likely be attributed to the doubt that they had about others' decisions. In addition, Acumen's users expressed doubt about the

credibility of the system's experts/mavens, and skepticism of experts as compared the complete community of users has been replicated in other experiments as well (Chen, 2008; Senecal & Nantel, 2004).

Doubt about others' information or knowledge and, subsequently, their decisions can arise from many different sources. An individual may doubt that others have information or knowledge that they do not, or he may doubt that others used their information or knowledge to make informed decisions. This doubt about the community data often reduces the social influence of the community data, and hence this effect runs counter to the cascade effect that is created by capturing decisions rather than knowledge. Nonetheless, people often still engage in cascade behavior, indicating that doubt about others' information or knowledge does not completely mitigate the social influence of community data. In summary, then, multiple individual and contextual factors play a role in determining the strength of social influence that a system's community data exerts during an individual's decision making process.

### **8.1.3 Capturing Objective Information and Mitigating Informational Cascades**

While there are numerous challenges that surround the processing of objective information in social navigation systems, capturing information is likely the most salient one because it can mitigate informational cascades in social navigation systems substantially. Moreover, because informational cascades occur in social navigation systems applied to both objective and taste-based domains, more effective capturing of information could benefit all social navigation systems.

Irrespective of whether personalization is desirable, cascades cannot be mitigated by simply by using more complex social navigation systems. As Chapter 3 discusses, all types of social navigation systems are susceptible to herding and

cascade behavior. By presenting community data, irrespective of what algorithm was used to aggregate it, a social navigation system becomes susceptible to cascades due to the informational influence that its community data exerts.

In this section, I discuss two methods for potentially mitigating cascades: via algorithmic strategies and via user interaction techniques. Given the challenges associated with using algorithmic strategies to mitigate herding, I argue for a novel approach to mitigation that employs user interaction. Ultimately, these approaches will likely prove complementary.

#### 8.1.3.1 Mitigating Cascades via Algorithms

Recent research demonstrates that algorithmic approaches can yield a manipulation-resistant recommender system by limiting the influence of users whose ratings have proven to be inaccurate and thus potentially malicious (Resnick & Sami, 2007). Similarly, there is algorithmic research on networks that has studied where to place detectors to identify cascades in the network (Leskovec et al., 2007) and how best to start cascades (Domingos & Richardson, 2001).

While these approaches provide a foundation for approaching cascade mitigation via algorithms, it is unclear how applicable they are to mitigating cascades in social navigation systems. Many informational cascades are started inadvertently and not through manipulation, and there is no evidence that particular individuals start cascades more often than others. Moreover, it is unclear whether a network perspective is appropriate for social navigation systems.

Putting these concerns aside, the question is whether an algorithm might be able to identify cascade behavior and discount it, leading to a more accurate depiction of the community's "best guess." The answer to this question is unclear.

Algorithmic approaches require substantial amounts of data in order to be effective, which means that a system must be actively collecting data for a long time before it becomes effective. Many privacy and security decisions, however, cannot or should not be deferred, as new threats often arise quickly and do significant damage in their early stages. For such threats, community data is needed immediately rather than later.

Thus, there are difficult tradeoffs between (a) requiring users to make unaided decisions and collecting but hiding this data for a period of time in order to ensure the community data is accurate and (b) showing users limited, potentially inaccurate community data from the start, which will sometimes improve their decisions but also occasionally lead to cascades that have significant negative consequences.

Another distinct weakness of using history-based data to compute on community data is that users must maintain stable identities in order to determine which, if any, users are most likely to start or propagate cascades. This weakness requires consideration of another tradeoff: users must forfeit some measure of privacy in order to improve the accuracy of community data so that it is useful for decision making.

Using a reputation system (Resnick et al., 2000) could incentivize users to forego some measure of privacy in order to build and maintain a reputation for making good decisions. The challenge for such a system is developing appropriate incentives to reward good decisions and a good reputation.

#### 8.1.3.2 Mitigating Cascades via User Interaction

A promising—and so far unexplored—avenue of research is to mitigate cascades via user interfaces techniques. The general goal of these techniques should be to balance two competing goals: (a) enabling users to leverage



community data and (b) capturing user information and expertise in order to provide more accurate community data and thus mitigate informational cascades.

Today's social navigation systems afford easy use of community data but sacrifice accuracy. In contrast, imagine a user interface that afford somewhat limited use of community data in order to ensure that a system can capture some measure of users' information or knowledge during decision making and hence maintain the accuracy of the system's community data.

For example, instead of displaying a system's community data, a user interface could provide an additional choice labeled "go with the community decision" alongside other choices. If a user chose to go with the community decision, her decision would be the community's consensus; more importantly, her decision would not be added to the system's community data because the decision does not contribute new information to the system.

Another option is a two-stage decision process. During the first stage, the interface would present a user with her potential choices but not show any community data. Making a choice would lead her to the second stage, where the interface would show the community data and allow her to change her decision if she wants. In this design, the user's initial decision would be included in the community data because it is uninfluenced by community data.

Of course, these approaches are quite rudimentary and rigid, and it is unclear whether users would accept and acclimate to more restricted and less straightforward uses of community data. However, they demonstrate the potential of an informational cascades perspective to inform the design of novel interfaces for social navigation applied to privacy and security management.

**Table 8.1** Characteristics of community data.

	<b>Collection</b>	<b>User Burden</b>	<b>Aggregation</b>	<b>Information Capture</b>
<b>Activity Data</b>	Implicit	Low	Easy	Low
<b>Ratings</b>	Explicit	Moderate	Easy	Moderate
<b>Free Text</b>	Explicit	High	Hard	High
<b>Tagging</b>	Explicit	Moderate	Moderate	Moderate-High

It is also worthwhile to consider how different types of community data impact the frequency of cascades. Table 8.1 characterizes four popular types of community data—activity or behavioral data, ratings, free text, and tagging—along four dimensions: (a) whether the collection of data require explicit actions by users; (b) the degree of user burden in collecting the data; (c) the difficulty in aggregating the information; and (d) the ability of the type to capture information or knowledge.

The *information capture* trait characterizes how much information the data type conveys to users; more expressive data conveys more information and thus is easier to understand and use. There is a correlation between the ability of a data type to capture information and the likelihood of informational cascades occurring: the more information captured, the less likely informational cascades are to occur because it is easier to understand why a user made a particular decision. This is an important correlation.

Characterizing community data types by their level of information capture helps explain findings from Acumen and Bonfire. The cascades that occurred in Acumen are partially a result of its use of activity data. Bonfire’s use of both activity data and tagging was well received because those data types complement each other. Activity data is simple and always present, and tagging can

complement the activity data by providing a more expressive form of data, albeit at the cost of an increased burden on users.

What can be learned from this characterization of community data is that there are tradeoffs in choosing to use different types of community data. Activity data and free text lie on opposite ends of a spectrum in which the tradeoff is between ease of collection & aggregation and expressiveness & cascade mitigation. Activity data is very easy to collect and aggregate but has very low expressiveness and hence is likely to cause more cascades. In contrast, free text is difficult to collect because it places a high burden on users and is hard to aggregate, but it is very expressive and is less likely to lead to cascades. Ratings and tagging occupy the middle of this spectrum, and the difficulty in collecting and aggregating these data types is commensurate with their expressiveness and likelihood of preventing cascades.

Another tradeoff to consider when choosing the types of community data to use in a social navigation system for privacy or security management is users' motivation. The higher the user burden that a system places on users, the more motivation is needed for users to contribute data. Thus, it is important to choose a community data type that matches users' motivation. There are many potential methods to motivate users, including direct payment, reputation building, game playing, and public service.

## **8.2 A General Approach for Evaluating the Social Influence of Social Navigation Systems**

The experimental design employed in the nonprofit choice experiment is largely agnostic toward both system functionality and domain. As such, it can serve to inform a general approach for evaluating social navigation systems applied to domains where users employ objective information to make decisions.

This approach can measure the strength and type of social influence for a social navigation system's community data, the strength of influence imparted by particular facets of community data (e.g. size, unanimity, personalization), and the strength of influence for particular vectors of community data (i.e. influence based on the directionality of community data).

Four steps summarize this general evaluation approach:

- (1) identify the decision that the social navigation system will support and the most influential information source(s) in a domain;
- (2) develop a framework to systematically vary and provide incomplete and imperfect objective information to participants;
- (3) identify critical and contrasting decision points in the space of objective information and community data;
- (4) analyze decision data from the chosen decision points to measure:
  - a. the type and strength for the community data's social influence;
  - b. the strength of influence that characteristics of community data (e.g. size, unanimity, expertise, personalization) impart;
  - c. the strength of the community data's social influence based on its directionality;

Using an example drawn from the health domain, I discuss each of these steps in turn. Finally, I discuss the benefits and limitations of this framework.

### **8.2.1 Identifying a Decision and the Most Influential Information**

#### **Sources**

The first step in preparing to evaluate a social navigation system in a domain with objective information is to identify the decision that the system will aid and

the objective information sources that users may employ when making this decision. In the nonprofit choice experiment, the decision supported is whether to make an online donation to a nonprofit organization. It is best if there are relative few choices for the decision, and an important feature of a decision is whether there is a default or cost-free choice. The nonprofit choice experiment employed a decision with a cost-free choice; in contrast, when an individual is choosing between two new restaurants, there is no default or cost-free choice. I discuss how the presence of a default choice impacts the evaluation below.

The example decision employed during this discussion is whether to start taking particular vitamin supplements. This is the general decision type, and each particular decision in the experiment would ask participants to decide whether they would take a particular supplement. This decision has a default, cost-free choice: to continue to abstain from taking any supplements.

In addition to identifying the decision to support, it is necessary to identify one or two information sources that individuals often employ to make the decision. In the nonprofit choice experiment, participants had access to a single information source—watchdog ratings—that donors frequently employ when deciding whether to make a charitable donation. For the vitamin supplements example, it is assumed that individuals use information from news articles to decide whether to start taking a supplement.

### **8.2.2 Developing a Framework for Providing Incomplete Information**

In order to distinguish between normative and informational influence, participants must hold the beliefs that (a) they have incomplete or potentially inaccurate information and (b) that other people may have information that they do not. When individuals hold these beliefs, they have motivation to seek out information from the community data, thereby creating the opportunity for

community data to exert informational influence. Of course, the primary motivation for a decision will determine whether community data exerts normative or informational influence.

Informational cascade experiments and social influence experiments use different techniques to impart these beliefs. In informational cascade experiments, the standard way to impart these beliefs is to enable participants to select and privately view one piece of information from amongst three pieces of equal information; participants quickly come to understand that each individual has a random and incomplete piece of information (Anderson & Holt, 2006). In social influence experiments, these beliefs are imparted simply by virtue of observing others' decisions; the experiment is often set up so that others' decisions conflicts with or casts doubt on the expected choice.

In the nonprofit choice experiment, I drew from both types of experiments to convince participants that they have incomplete information and that others may have complementary information. A series of examples at the beginning of the nonprofit experiment imparts these beliefs by creating the expectation that watchdog ratings may be temporarily unavailable for standard reasons, and hence participants may see only one or two ratings rather than all ratings. Descriptions of the watchdog ratings and community data reinforce the potential unavailability of ratings and the potential for different participants to see different ratings. In addition, many of the scenarios (decision points) in the experiment cast doubt on the expected choice by providing contradictory information.

Imparting these beliefs on individuals is easier in real-world situations because individuals can readily imagine information that others may have. However, it is difficult to impart this belief in an experimental setting because an experimental

setting is constrained, and thus participants can often anticipate information sources and availability more easily. It was especially difficult to impart these beliefs in the nonprofit experiment because an experiment administrator was not present to answer and clarify questions. To effectively impart these beliefs, I performed numerous pilot studies of the nonprofit choice experiment to refine (i) the flow of and language in the initial examples and (ii) descriptions of the ratings and community data in the trials themselves. Imparting these beliefs is necessary for the experiment to succeed, and hence this step cannot be overemphasized.

In the running example for choosing vitamin supplements, the most reasonable approach is to mirror nonprofit ratings by constraining the information in the experiment to be three *Yes* (take the supplement) or *No* (do not take the supplement) recommendations that are derived from three newspaper articles. In each decision trial, then, a participant would see the recommendation(s) from one or more articles. A more complex experiment might add a unanimity component to the recommendation (e.g. “70% of people benefit from taking this supplement”), an element of risk to the recommendation (e.g. “recommended, but 33% of people experience minor negative effects from taking the supplement), or use different media to convey the information (e.g. print vs. video).

### **8.2.3 Identifying Critical and Contrasting Decision Points**

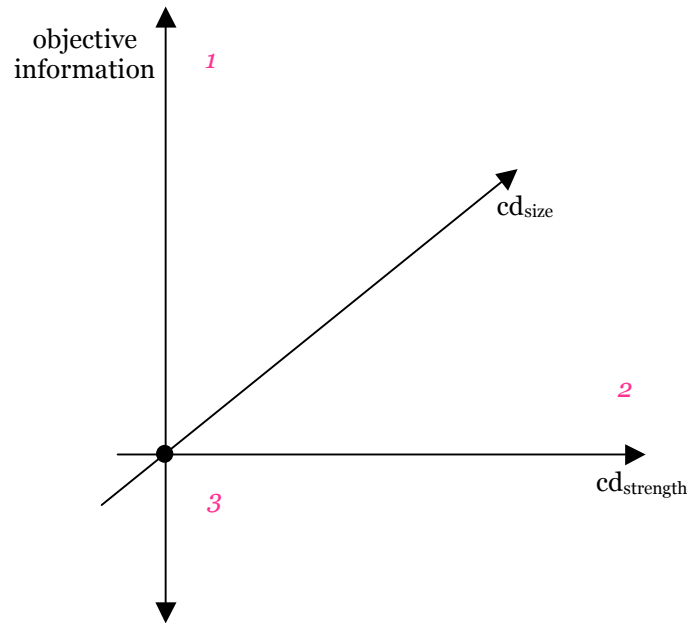
The next step in the general experimental method is to identify decision points from which to collect decision data. Identifying decision points is accomplished by mapping out the space of possible decision points and then selecting important decision points.

Two sets of independent variables define the decision space: the objective information and the facets of community data to be studied. Within this space are

decision points that will serve as scenarios. Figure 8.1 shows the decision space for the nonprofit choice experiment. There are three axes: objective information (watchdog ratings), community data size, and community data unanimity. Three decision points are labeled in Figure 8.1 which illustrate different points in the space. At point 1, there is much objective information but very limited community data; the information and community data agree or suggest the same decision. At point 2, there is little objective information, much subjective information, and the information and data again agree. Finally, at point 3, there is limited objective information and community data, and the information and data disagree (hence the negative value of information and positive value of community data).

The decision space in Figure 8.1 can be adapted to other decisions and domains. This decision space depicts a single type of objective information, but multiple axes could be used for experiments where there are multiple types of objective information. The community data axes can be adapted to map out any attributes or presentation of community data.





**Figure 8.1** Decision space for nonprofit choice experiment.

There are three types of important decision points: baseline, critical and contrasting. For baseline points, participants should see only objective information and not community data. Decision data from baseline points provide the signal strength of the information, and this signal strength can later be compared to the social influence of the community data. Critical decision points are those that present difficult or unique decisions to participants. Contrasting decision points employ different values for a characteristic of the community data, such as the size or unanimity of community data. Decision data from contrasting decision points can be used to investigate the impact of a community data characteristic.

In the nonprofit choice experiment, I identified critical decisions as (i) those where the community data suggested one decision and the ratings suggested another decision and (ii) those where the suggested decision was *Yes* rather than *No*. These are generally good decision points for which to gather data. Comparing decision data for points where the community data and objective information

disagree makes it possible to determine whether the community data is exerting normative or informational influence. Comparing decision data for points in which a particular choice is suggested affords measurement of the community data's strength of social influence for different choices.

There are many different attributes of community data that might impact its effect on decision making. Data from the nonprofit experiment shows that both size and unanimity exert an effect on people's decisions, but a full understanding of how the spectrum of sizes and unanimity impact people's decisions requires additional decision data. Another common attribute of community data is personalization; it is unclear when and for what circumstances personalizing community data increases its impact. Finally, user interfaces that display recent data and trends within the community data are also fruitful facets to explore.

Let us return to our example, where a social navigation system is to help users decide whether to take new vitamin supplements. The critical decision points for this experiment should mirror those of the nonprofit experiment. Decision data should be collected when the available information and community data disagree, both when the community data suggests *Yes* and when it *No*. Decision data should also be collected when the community data and available information disagree and for both possible choices.

Selecting attributes of community data to evaluate is more subjective. Because there are so many small nonprofits, it is expected that most nonprofits would likely have limited community data. Hence, the nonprofit choice experiment collected decision data when participants had limited community data. In contrast, a quick scan of drug reviews on WebMD shows that many drugs have significant community data, suggesting that vitamin supplements may have many reviews as well. Thus, evaluating larger sizes of community data may be more

useful for a social navigation system for vitamin supplements. Health information can change quite quickly, and either recency or trend characteristics of community data would likely have an impact on users' decisions and thus are good attributes for evaluation. Finally, expertise certainly plays a role in how health information impacts decisions, and hence it is another characteristic of community data that could be evaluated for this social navigation system.

#### **8.2.4 Evaluating Decision Data**

By setting up the experiment using the guidelines discussed above, the decision data obtained from the chosen decision points are amenable to the same analysis that I performed in the nonprofit choice experiment. Specifically, the following analyses can be performed:

- the type of social influence that community data exerts—informational or normative;
- the strength of social influence that community data exerts when different amounts or combinations of information are available;
- the strength of social influence that community data exerts for different choices and any biases that participants have;
- the effects that characteristics of community data have on participants' decisions.

#### **8.2.5 Benefits of an Evaluation Framework based on Social Influence**

Existing evaluation techniques for social navigation system includes measuring the increase in speed or efficiency that is achieved by when users employ a social navigation system (Wexelblat & Maes, 1999), measuring subjective satisfaction with community data (Svensson et al., 2001) and recommendations (Cosley et al.,

2003), measuring the accuracy of recommendations (Herlocker et al., 2004), and views or downloads of suggested items (Cosley, Lawrence, & Pennock, 2002).

The implicit assumption that motivates these evaluation techniques is that they are useful for determining the effectiveness of a social navigation system. However, they suffer from two distinct weaknesses. First, these techniques record measurements that are proxies to the desired measurement, the effectiveness of a social navigation system. Recent research argues that more focus is needed on the usage of social navigation systems as compared to these proxy measurements (Herlocker et al., 2004; McNee, Kapoor et al., 2006; McNee, Riedl, & Konstan, 2006a; McNee, Riedl et al., 2006b), and I concur with this argument. Another weakness of these evaluation techniques is their diversity; because they are quite different, the data that they yield cannot be readily compared.

Evaluating a social navigation system using social influence can address the weaknesses of other evaluation techniques. Decision data that measures the social influence of a system provides insight into how a system's community data influences users' decisions, and thus social influence is a more direct measure of a system's impact on users' decision processes rather than measuring a proxy.

Evaluating social navigation systems using social influence also affords direct comparisons across system functionality, across domains, and even across academic disciplines. Measurements of social influence quantify the impact that a system's community data has on users' decisions using system-independent and domain-independent measures, and hence the framework is agnostic with respect to how the system captures, aggregates, and displays community data. For instance, the social influence of a system that employs simple aggregation algorithms such as counting can be compared to the social influence of a system that employs collaborative filtering. In addition, social influence measurements

can be used to compare user interface features for a social navigation system by comparing how different features change the social influence that the system exerts on users' decisions.

Evaluating social navigation systems using social influence affords comparison of social navigation systems across domains. Using an evaluation method based on social influence abstracts and standardizes the inputs to users' decision process—available information and community data—and does the same for its outputs—the social influence of a system's community data and factors that impact the strength of the influence. Thus, an evaluation method based on social influence prescribes collection of the same decision data and similar analyses of the decision data for each system. For instance, the social influence of Acumen and Bonfire can be compared to the social influence found in the nonprofit choice experiment.

Such comparisons are valuable because there is ongoing debate about when and where to employ social navigation systems (Dieberger et al., 2000), but there is little guidance beyond case studies about the utility of social navigation systems in different domains. An evaluation method using social influence affords comparisons of evaluation data across different domains and can help determine when and where social navigation systems are most useful.

A final benefit derived from evaluating the social influence of social navigation systems is the opportunity to compare evaluation data of social navigation systems and behavioral data from relevant psychological and economic experiments. The foundation of this thesis is the claim and supporting arguments that the social navigation user experience can be characterized by employing relevant perspectives from the behavioral and social sciences. It is logical, then, to draw parallels between and compare results from social influence measures of

social navigation systems and results from social influence, advice-taking, and informational cascade experiments.

By connecting evaluations of social navigation systems to social influence, advice-taking, and informational cascade experiments, there is the potential to advance all bodies of research. One benefit for social navigation systems researchers is the adoption of techniques from related disciplines to the study of social navigation systems; the experimental design in the nonprofit choice experiment demonstrates the value in this approach.

Another potential benefit for social navigation systems researchers is the improvement of social navigation systems through the application of findings from social influence, advice-taking, and informational cascade experiments. Interactive computation affords new and more powerful applications of social influence, often via social navigation systems; computation simplifies and provides flexibility in all facets of social information usage, from collection to aggregation to display. As such, social navigation system designers can draw from the results of social influence and informational cascade experiments to enhance the utility of social navigation systems.

Finally, social navigation systems may also be able to provide insights into the basic mechanisms of social influence and informational cascades by providing behavioral data more quickly, more easily, or in domains or situations that psychological and economic experiments cannot easily explore. Thus, there is potential for social navigation systems to provide behavioral data for the study of basic psychological and economic phenomena.

### **8.2.6 Limitations of an Evaluation Framework based on Social Influence**

The limitations of an evaluation framework that measures the social influence of social navigation systems center on its inability to identify and collect decision data for the decision points that users most often encounter. Recall that the objective information and features of community data that users employ when making decisions define the space of possible decisions (also see Figure 8.1). Thus, while decision data can be collected for any decision points in the decision space, the decision data that is most valuable and necessary for accurately assessing the impact of a social navigation system cannot be determined via an evaluation framework that measures social influence. Hence, a social influence evaluation framework cannot, by itself, fully assess the impact of a social navigation system.

The framework can, however, provide insight into what data is needed to complement the framework and ultimately foster its success. In particular, complementary data that indicates the decisions points that users are most likely to encounter can suggest the decision points for which to collect and analyze decision data. The key questions that arise when endeavoring to determine the most frequently encountered decision points are:

- what objective information do users typically have when making decisions?
- what community data are users likely to have when making decisions?
- what order will users often encounter decision points?

Addressing these questions will indicate which decision points in the space are most frequently encountered; decision data gathered from these points can provide a more accurate evaluation of a system than can decision data from other points.

The distribution of objective information can vary markedly across user populations and domains. In end-user digital privacy and security management, for instance, the level of information or expertise among users is often uniformly low. In contrast, consider a healthcare domain, where there can be a bimodal distribution of information between trained healthcare professionals and patients. Finally, in the nonprofit giving domain, half of all donors and more than 60% of large donors report that they consider financial efficiency information an important factor when making donation decisions (Princeton Survey Research Associates, 2001). The amount of objective information that users possess or gather bears on the decision points that users are most likely to encounter.

Like objective information, the amount of community data available when making a decision can vary markedly between domains and will influence the decision points that users will encounter most frequently. Analysis from Acumen's deployment shows that community data can often be obtained for the most popular websites but is quite difficult to collect from less popular websites; this is likely due to the power law distributions found in website popularity (Goecks & Mynatt, 2005a). Thus, when power law distributions are present in popularity, usage, or viewing habits of a user community, users are likely to find that each item has either a significant amount of community data or very little. Not all domains exhibit power law distributions; as noted in section 8.2.3, there are a limited number of prescription drugs, and hence most drugs have a large amount of community data regardless of their relative popularity. End-user security management may also have unique community data distributions because often users are forced to make decisions about new software or software updates. In such cases, there may be limited community data because the item is new and thus not many others have interacted with it.



So far, this discussion has focused on identifying the decision points that users are most likely to encounter given the information distribution and community data distribution within a domain for a given point in time. However, it is also necessary to consider the *trail of decision points* that are likely to arise as a community of users makes a sequence of choices. This trail will play a role in determining both the community data available for any particular decision point and, consequently, the subsequent decision point and continuing trail as well. Clearly, the process by which a community creates a trail through a decision space is quite complex, and only a brief examination of this process is possible in this dissertation.

There are numerous open questions about a trail of decision points. One important question is whether early decisions exert more influence than later decisions over the trail's trajectory. A related question concerns the degree to which trails can be substantially changed or manipulated by a small group of individuals. Lastly, it is important to ask whether a system produces many similar trails or whether the trails within a system are more varied and, if so, what can explain the variations in a system's trails.

In summary, the limitations of evaluating a social navigation system using social influence are rooted in its evaluation of particular decisions rather than a trail of decisions. To evaluate social influence, it is necessary to identify and collect decision data for particular decision points. This decision data is gathered without regard to contextual and temporal factors—information distribution, community data distribution, and the dynamics between decision points—that lead to, follow, and connect decision points along a trail. These factors will dictate which decision points users will encounter most often, and hence which decision points should be the focus of evaluations. In addition, these contextual and temporal factors may impact the decisions themselves. For instance, economic

research suggests that people do adapt their use of community data over multiple instances but do so only in constrained situations (Hussam, Porter, & Smith, 2008).

Ultimately, a more complete evaluation of decisions supported by a social navigation system is likely to require pairing the general method for evaluating social influence discussed in this chapter with a more dynamic method in which authentic community data is employed and sequences of decisions are captured and studied. Iterative application of these methods could be used to investigate both trails of decisions points and particular decision points and to connect them in meaningful ways.

## **CHAPTER 9**

### **IMPACT AND FUTURE WORK**

I conclude this thesis with a discussion of its impact, and I chart out future work that follows the trajectory initiated in this thesis.

#### **9.1 Impact**

The goal of this thesis is to develop a better understanding of the social navigation user experience. Each chapter makes a contribution toward this goal.

In Chapter 2, I employ a user-centered perspective to identify four challenges for improving social navigation systems. These challenges are (a) creating and understanding systems for the purpose of supporting the canonical activity in social navigation, decision making; (b) applying social navigation systems to domains with objective knowledge; (c) understanding how users employ community data to make decisions; and (d) evaluating the efficacy of social navigation systems.

Chapter 3 discusses how herding behavior can act as a lens for further refinement of these challenges. Herding behavior has occurred in numerous social navigation systems and is quite striking, and thus it has been documented in some detail. Herding arises from the decisions that users make using knowledge available to them and using a system's community data. Herding suggests that a system's community data exerts social influence on users, and evaluations of herding behavior indicate that herding can lead to surprising, suboptimal, and undesirable outcomes both at the individual level and the community level.

Chapter 4 synthesizes social navigation systems research with research in social influence, advice-taking, and informational cascades to develop hypotheses about the social navigation user experience. These hypotheses posit that community data from a social navigation system exerts informational influence on users, that users egocentrically discount community data, that herding in social navigation systems can be characterized as informational cascades, and that the size and unanimity of the community data correspond to the strength of the community data's influence. These hypotheses comprise the thesis statement as well.

Chapter 5 employs this initial understanding of the social navigation user experience to analyze two social navigation systems, Acumen and Bonfire. Acumen is a social navigation system that helps end users make privacy management decisions, and Bonfire is a social navigation system that helps end users make security management decisions. This chapter reflects on the mixed results obtained with Acumen and Bonfire and discusses how minimal expertise among users and informational cascades present challenges to the successful application of social navigation to end-user security and privacy management.

Chapter 6 describes the design of the nonprofit choice experiment. The goal of this experiment was to evaluate the hypotheses about the social navigation user experience developed in Chapter 4. I based the experiment's design on social influence and informational cascade experiments, and hence the experiment features charitable giving scenarios in which a participant employs both available knowledge and community data to decide whether she would make a donation to a nonprofit organization. A significant portion of the experiment's design is devoted to identifying decision scenarios that afford evaluation of the hypotheses for the social navigation user experience.

Chapter 7 discusses results from the nonprofit choice experiment. The experiment's results support the majority of the hypotheses about the social navigation user experience and provide mixed evidence for the other hypotheses. The results show that the social navigation system's community data exerted informational influence on participants and that the herding in social navigation systems can be characterized as informational cascades. The results suggest that participants egocentrically discounted community data; however, because the experiment was not designed to directly measure egocentric discounting, it is not possible to verify this hypothesis. The experiment's results show that the unanimity of the community data is a significant factor in the effect that the community data has on participants' decisions, but that the size of the community data was only significant in some instances. Finally, the results indicate that participants were skeptical of making a donation in general, and the community data was much more influential when reinforcing this skepticism as compared to overcoming it.

Chapters 2 through 7 develop a robust understanding of the social navigation user experience, and Chapter 8 discusses the implications of this understanding. Broadly, these implications concern improving the design of social navigation systems and developing a general framework for evaluating the social influence of social navigation systems. The approach to improving social navigation systems is grounded in the development of methods to capture, aggregate, and represents objective information rather than actions or decisions. A general framework for evaluating the social influence of social navigation systems derives from the experimental design of the nonprofit choice experiment; this framework standardizes the inputs, outputs, and analyzes for social navigation systems. The benefits of this framework include comparing social navigation systems within and across domains and comparing results from evaluations of social navigation

experiments to results from experiments in social influence and informational cascades. However, this framework is limited because additional information is needed to identify the most frequent or salient decision points for which to collect and analyze decision data. This additional information is necessary to ensure that the framework provides an accurate assessment of the system's impact on users' decisions.

## **9.2 Future Work: Addressing a Spectrum of Decisions**

One trajectory of future work is an exploration of the *decision path* that users traverse from initial formulation of a question or decision to their final choice. A user's decision path is the series of decisions that he makes from the initial question to final decision that is often permanent or quite difficult to reverse. Recall that, in the nonprofit choice experiment, users were asked to decide whether they would make a donation to a nonprofit organization. This is a final decision, and there are often many decisions a user makes before arriving at this final decision. Imagine a user has decided that he would like to make a donation to an after-school education program; this decision opens up a space of options—he can donate locally or nationally, to low-income or minority students, to math or literacy education—and he must make decisions to navigation this space just to arrive at a final decision.

The conceptualization of a decision path connects the fundamental unit of analysis in this thesis—a decision—to the process of navigating, which is central to the body of research in social navigation systems. Navigating, then, is the process of making repeated decisions in order to arrive at a final decision, and the decision path is the sum of those decisions. By defining navigation as a repeated decision making, it is likely that the understanding of the social navigation user

experience developed in this thesis can be used to better understand the types of decisions that users make as they create a decision path.

One challenging aspect of a decision path is that users often encounter many different types of decisions. Decisions may differ based on the number of choices, the difficulty in reversing a decision, whether previous decisions impact or bias current decisions, whether the decision requires use of objective knowledge, and in other ways as well. Cataloging decision types and understanding how different social navigation systems and different features of systems support some decisions more readily than others would be a significant step forward in the use of social navigation systems to support users' goals.

### **9.3 Future Work: Towards Mindful Use of Social Navigation Systems**

This thesis suggests that it is overly simplistic to view a social navigation system as a source of additional information to support decision making. Instead, this thesis demonstrates that community data from a social navigation system often exerts strong influence over users' decisions, and that this influence can lead to surprising outcomes. Community data's influence is often significant enough to cause people to ignore contradictory knowledge or information and instead engage in herding behavior. In addition, the influence of community data can be non-uniform and counterintuitive. For example, in the nonprofit experiment, the community data reinforced participants' bias against making a donation but did not help participants overcome this bias. Ultimately, then, the presence of community data led participants to withhold charitable donations more often than they otherwise would have. Depending on the perspective taken, the impact of community data on nonprofit giving may be considered undesirable or detrimental to societal goals.

Social navigation systems, then, are not neutral technologies; instead, they promote some behaviors and outcomes and mitigate others. This perspective runs counter to past research, which argues that social navigation systems enable users to shape a digital space and guide future activities (Dieberger et al., 2000; Harrison & Dourish, 1996). Furthermore, this past research argues that social navigation systems are a blank slate that users shape. In fact, the research in this thesis demonstrates that this is not true; the sociotechnical system that surrounds a social navigation system plays a significant role in shaping the use of the system. Knowledge distribution, community data distribution, decision biases, and incentives all influence the use of a social navigation system, and it is these factors that often cause a social navigation system to exert unequal impact on users' decisions. Moreover, social navigation systems can amplify social influence, and hence they can amplify the unequal impact. Such amplification can lead to markedly skewed influence, as was the case on the nonprofit choice experiment.

### **9.3.1 The Intent and Goals of Social Navigation Systems**

Due to the strong influence of social navigation system on users' decisions and unequal outcomes that arise from that influence, it is useful to draw a parallel between social navigation systems and persuasive technologies (Fogg, 1998). A persuasive technology is an interactive technology designed with an intent to change attitudes or behaviors. Because many computing systems can change attitudes or behaviors, the notion of *intent* is critical to the definition of a persuasive technology because it derives from the goal of or purpose for the persuasive technology.

Collaborative computing systems are not traditionally considered to be persuasive computing systems; nonetheless, persuasive computing and intent



may be a fruitful perspective for social navigation systems. Before deploying a social navigation system, it may be useful to identify the system's intent and the metrics for evaluating whether that intent have been accomplished. Explicit focus on a system's intent can help administrators, designers, and other decision makers identify (a) what benefits may accrue and what drawback may occur from use of a system and (b) which stakeholders benefit and which are harmed from use. Identifying and analyzing the benefits and drawbacks for a system can inform the design, deployment, and evaluation of a social navigation system.

Social navigation systems often have many stakeholders, and this is especially true of commercial systems. Understanding the benefits and drawbacks of a system can promote a discussion about how best to maximize the utility of a social navigation system across its stakeholders, and this discussion can lead to more informed and mindful use of social navigation systems.

A first approximation of stakeholders for a social navigation system includes its users, its administrator or administrating organization, and organizations that may benefit from users' behavior. Furthermore, a key question to address is whether the administrator's intent conflicts with users' goals; such conflict can make the deployment and use of a social navigation system more difficult.

Academic researchers have deployed systems such as Footprints (Wexelblat & Maes, 1999), Kalas (Svensson et al., 2001), and Movie Lens<sup>28</sup> with the intent to develop knowledge about how users employ social navigation systems and how they can be improved. In these systems, then, administrators' intent does not conflict with users' goals.

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<sup>28</sup> <http://www.movielens.org>

However, administrators' intent and users' goals can conflict in commercially-operated social navigation systems, such as those present on Amazon<sup>29</sup> and the website for *The New York Times*<sup>30</sup>. Consumers do not pay for access to these sites' community data, and hence administrators' intent of the social navigation systems for these sites likely driven in part by a profit motive. For instance, the intent of Amazon's social navigation systems may be to encourage users to buy items; for *The New York Times*, the intent may be to encourage users to visit and read more articles in order to boost advertising revenues.

For commercially-operated social navigation systems, then, there are potentially dual intents: to help users make better decisions and to promote particular behaviors or outcomes that benefit the system's operators. Often these intents align: a search engine provides relevant search results and ads to help a user find information; users, in turn, are more likely to use the search engine repeatedly and click on ads, both of which generate profit for the search engine.

However, there are also instances where individual goals and company or administrators' intent do not align. For instance, informational cascades frequently benefit organizations but not individuals. Organizations profit from cascades through the consumption behavior that a cascade drives, but many individuals may regret seeing a popular but low-quality movie, donating to a trendy nonprofit organization, or partaking in the latest fad diet.

The divergence of administrators' intent and user goals for a social navigation system is potentially problematic because administrators usually have significantly more power than users and because administrators often have a profit incentive to leverage that power. An organization can take advantage of

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<sup>29</sup> <http://www.amazon.com>

<sup>30</sup> <http://www.nytimes.com>

this power in seemingly benign ways, such as by ignoring cascades or ignoring features that would mitigate cascades. Of course, an organization could actively promote cascades as well, although this would be a relatively brazen course of action<sup>31</sup>. If the administering organization chooses to employ a system with the intent to maximize profits, it is possible that they will do so at the expense of individual and societal goals by allowing or promoting inaccurate informational influence and informational cascades.

The deployment of a social navigation system that leads to outcomes that are not in the best interest of individuals or society can occur under more benign circumstances as well. Many people assume that social navigation systems are beneficial because they provide additional information that is from unbiased sources. The research in this thesis demonstrates this is a false assumption, and the lack of an established evaluation framework for social navigation systems prevents the assumption from being easily disproved. Hence, social navigation systems can be deployed with good intentions yet ultimately lead to unexpected or undesirable outcomes.

### **9.3.2 Long-term Observation and Oversight of Social Navigation Systems**

Because administrators' intent may conflict with users' goals, it is useful to investigate methods that balance stakeholders' interests. Balancing interests

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<sup>31</sup> It is useful to draw a distinction between the manipulation that the organization controlling the social navigation system can perform and the manipulation of the system by entities to promote a cascade of a particular product, such as a movie or health supplement. The former type of manipulation is my focus and, to the best of my knowledge, has not been previously discussed; the latter has been investigated and potentially solved (Resnick & Sami, 2007)

includes maintaining incentives for stakeholders to participate but ensuring that no one stakeholder can take advantages of other stakeholders. One potential method for balancing stakeholder interests centers on long-term observation and oversight of social navigation systems.

Understanding and balancing stakeholder interests likely requires a deep knowledge of social navigation systems that researchers do not yet have. In particular, the dynamics of social navigation systems are not well understood. The research in this thesis investigates decision making for particular points, but the evolution of social navigation systems from point to point is complex and not well understood. Section 8.2.6 discusses some of the factors that influence the evolution of a social navigation system. In particular, to balance stakeholders' interests, data is needed to determine whether the intent of a system is being achieved and whether stakeholders' goals are being met. Long-term observation and measurement of social navigation systems is likely to provide data that can be used to address these questions.

Finally, a straightforward method to balance stakeholders' interest is oversight by a third party that is independent of the system's stakeholders. A third party could develop standards for social navigation systems and certify social navigation systems that abide by these standards. Oversight of financial markets is common and a necessary tool to sustain the use and benefit of markets. Many social navigation systems are much like markets—they are places where entities with potentially conflicting interests interact in such a way to exchange or share information or goods. Hence, oversight of social navigation system is a potentially reasonable step to ensure that social navigation systems are fair and useful for all stakeholders.

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## **VITA**

JEREMY GOECKS was born in Madison, Wisconsin on March 6, 1977. He spent his formative years in Monroe, Wisconsin and graduated from Monroe High School in 1995. Jeremy earned a B.S. in Computer Science, designated with Honors and Phi Beta Kappa, from the University of Wisconsin-Madison in 2000. He came to Georgia Tech in 2001 to pursue a doctorate in Computer Science. Jeremy is married to Michelle Young, and together they tend to two cats, Lucky and A.J., and an Australian Cattle dog, Sidney. Jeremy and Michelle enjoy traveling both within the United States—they have visited more than 25 national parks—and abroad, and they also play ultimate frisbee and goaltimate together.